PREDICTION OF END-TO-END SINGLE FLOW CHARACTERISTICS IN BEST-EFFORT NETWORKS

A Thesis

by

YASHKUMAR SHUKLA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2005

Major Subject: Mechanical Engineering

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Approved as to style and content by:

Alexander Parlos (Chair of Committee)	Won-jong Kim (Member)
Edgar Sanchez-Sinencio (Member)	Dennis L. O'Neal (Head of Department)

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ABSTRACT

Prediction of End-to-end Single Flow Characteristics
in Best-effort Networks. (May 2005)

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Chair of Advisory Committee: Dr. Alexander Parlos

The nature of user traffic in coming years will become increasingly multimedia-oriented which has much more stringent Quality of Service (QoS) requirements. The current generation of the public Internet does not provide any strict QoS guarantees. Providing Quality of Service (QoS) for multimedia application has been a difficult and challenging problem. Developing predictive models for best-effort networks, like the Internet, would be beneficial for addressing a number of technical issues, such as network bandwidth provisioning, congestion avoidance/control to name a few. The immediate motivation for creating predictive models is to improve the QoS perceived by end-users in real-time applications, such as audio and video.

This research aims at developing models for single-step-ahead and multi-step-ahead prediction of end-to-end single flow characteristics in best-effort networks. The performance of path-independent predictors has also been studied in this research. Empirical predictors are developed using simulated traffic data obtained from ns-2 as well as for actual traffic data collected from PlanetLab. The linear system identification models Auto-Regressive (AR), Auto-Regressive Moving Average (ARMA) and the non-linear models Feed-forward Multi-layer Perceptron (FMLP) have been used to develop predictive models. In the present research, accumulation is chosen as a signal to model the end-to-end single flow characteristics. As the raw accumulation signal is extremely noisy, the moving average of the accumulation is

used for the prediction. Developed predictors have been found to perform accurate single-step-ahead predictions. However, as the multi-step-ahead prediction horizon is increased, the models do not perform as accurately as in the single-step-ahead prediction case. Acceptable multi-step-ahead predictors for up to 240 msec prediction horizon have been obtained using actual traffic data.

To my grandparents, parents and sisters

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CHAPTER I

INTRODUCTION

A. Introduction

Recent explosion in Internet usage has exposed several limitations in its design. The Internet, at present, uses data-gram switches as a means of dynamically allocating network resources on a demand basis. This approach is more suitable for non real-time applications. However, the nature of user traffic in coming years will become increasingly multimedia-oriented which has much more stringent Quality of Service (QoS) requirements. The current generation of the public Internet does not provide any strict QoS guarantees, such as bounds on delay, jitter and packet losses.

Two approaches have emerged to tackle this problem. One method is to make provisions in the network, by admission policing or by reservation, such that strict QoS requirements can be satisfied. This requires modification or additions to the currently deployed network infrastructure. The second approach is more practical and requires that applications determine and adapt to network conditions so that application QoS at the end points can be maintained. Effective predictive control is one element of such an approach, and it can be designed to adapt an application to network conditions and hence, improve QoS delivered to the end-user.

Modelling of the system under consideration is the core step of any control problem. A model representing the important dynamics of the system is necessary to build an efficient controller that gives desired performance. The proposed objective of the present research is to predict single flow end-to-end characteristics in best-effort networks. Immediate motivation for creating predictive models is to improve

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the QoS perceived by end-users in real-time application, such as audio. Developing predictive models for best-effort networks would also be beneficial for addressing a number of other technical issues, such as network bandwidth provisioning, congestion avoidance/control to name a few.

B. Research Objectives

The main objective of the present research is to develop predictive models that can be used to estimate the end-to-end characteristics of single flows in best-effort networks. If accurate, this predictor can be used by a controller to adapt the source send-rate to changing network conditions in an anticipatory manner. As a result of the network delay, the controller will receive delayed information to generate the control actions. To compensate for this dead-time, the present research also explores performance of developed predictor for a certain future prediction horizon i.e. multi-step-ahead prediction. The thrust of this research is to compare different empirical models, linear and non-linear, and to select the ones that give the best results in terms of accuracy and prediction horizon. This research also explores the performance of generic predictive models, i.e. those that do not depend on specific end-to-end path.

C. Literature Review

1. Research in End-to-End Flow Measurement

Data used in developing a predictive model should contain the important characteristics of the best-effort network. As the Internet is a large and complex network of networks it is not feasible to perform controlled experiments directly on it. A variety of tools have been developed over the years to characterize end-to-end behavior of best-effort networks.

Real (REalistic And Large) [1] was the first simulator developed for studying the dynamic behavior of flow and congestion control schemes in packet switch data networks. The simulator takes as input a scenario, topology and protocols and produces statistics of packets lost, queuing delay at each queuing points and other similar information. X-sim [2] is another simulation tool to mimic behavior of the best effort network. X-sim, which is based on x-kernel, is mainly useful to develop and test network protocols and architectures.

Network simulator (ns-2)[3], developed by a network research group, is the most widely used tool for simulation in network research. Ns-2 is an event driven simulation engine and has a wide variety of protocols and traffic generation tools to capture the heterogeneity of best-effort networks. As ns-2 can capture important dynamics of a best-effort network, it is used to create the model used in the present research.

End-to-end Network Delay Emulator (ENDE) [4] is another useful tool to emulate end-to-end flows between two hosts on the Internet. ENDE is mainly developed to test new multimedia protocols in a realistic environment.

Although many simulators are available, none of them can accurately capture the precise behavior of a best-effort network, such as the Internet, because of the complexity and non-equilibrium conditions involved. There are many active and passive measurement techniques available on the Internet for characterization purposes. But most of the data available is for round-trip information. The main focus of the present research is to analyze one-way end-to-end flows.

Shared Passive Network performance Discovery (SPAND) [5] is a real-time measurement tool, which measures available bandwidth and packet loss rates from a collection of hosts to determine wide area network characteristics. Another organization named Reseaux IP Europeens (RIPE) network coordination center (NCC) [6] has been operating a system called Test Traffic Measurement (TTM) that measures key parameters of the Internet, i.e. one-way delay, packet loss and some other measurements. By using dedicated test boxes, TTM proactively and continuously monitors the connectivity of a network to the other parts of the Internet. Unfortunately, to obtain this data one must become part of the RIPE network. Bovy et al. [7] shows analysis of the RIPE NCC measurements.

In 1998, Yeom [4] developed the tools UPBAT and TPBAT for end-to-end flow measurement. These tools allows one to measure forward and reverse delays between the source and the destination thereby allowing one to obtain flow characteristics as a function of time using several parameters like the packet size and inter-departure time. The UDP Packet Behavior Analyzing Tool (UPBAT), measurement tool for UDP, is implemented as client-server program. The UPBAT tool has been used in the present research for measuring end-to-end flow characteristics.

Planet-lab [8] is a collaborative effort to create a distributed overlay based test-bed for conducting Internet scale experiments and for developing new network services. Network services deployed on the Planet-lab experience all of the behavior of the real Internet. In the present research, one-way end-to-end flow characteristics are collected for modelling purposes from various nodes on the Planet-lab network.

2. Research in Estimation of End-to-End Flow Characteristics

Paxson and Floyd [9] clearly mentions the three key properties of the Internet that make it difficult to model and simulate its dynamics. These properties are immense changes over time, rapid geographic growth over time and the significant technical and administrative heterogeneities.

Very few tools have been developed to estimate the dynamics of the best-effort network, if any. Modelling best-effort networks has been normally approached from a statistical point-of-view [10]. A lot of queuing theory has also been applied for modelling the dynamics of best-effort networks [11]. Wolski et al. [12] has proposed a distributed system named Network Weather System to monitor network conditions and then forecast them for a certain time frame. This tool forecasts performance metrics like aggregate bandwidth and flow-averaged latency for TCP/IP networks.

Jain [13] suggested delay-based approach for congestion avoidance. In this approach, increase in packet delay is used as an indication of congestion to create efficient congestion control mechanism. Paxson [14, 15] has measured and analyzed end-to-end packet dynamics in the Internet. Bolot [16] also studied end-to-end packet delay and its loss behavior in the Internet. These researches emphasized that the Internet traffic conditions are not in equilibrium. Paxson [17] attributes failure of Poisson-modelling in capturing dynamics of Wide Area Network (WANs) to the bursty and heavily tailed traffic of the Internet. Such dynamic and non-equilibrium traffic conditions are one of the main reasons for the failure of statistical and queuing theories in modelling WANs.

Ohaski [18, 19] presented a novel and innovative approach to model the dynamics of best-effort networks. This approach assumes the Internet to be a “black-box”, as seen by the source and the destination, and the end-to-end packet delay dynamics are modelled using empirical modelling tools from System Identification. Ohaski [18, 19] used an Auto Regressive Exogenous (ARX) model for modelling a 100 Mbps LAN network. This is an approach towards building systems and architectures that are end-to-end rather than network-centric. The advantage of an end-to-end approach is that any analysis and methods developed for one system can be used by any other system, irrespective of the existing network infrastructure.

System identification techniques have been found to solve many complex engineering problems [20, 21]. Linear system identification models, like the ARX and the Auto Regressive Moving Average Exogenous (ARMAX) models, assume the dynamic relationship between system inputs and outputs to be a linear regression. However, complex problems involving nonlinearities may not be solved accurately using linear methods. Artificial Neural Networks (ANNs) have been shown particularly useful in predicting the dynamics of non-linear systems [22]. Feed Forward Multilayer Perceptron (FMLP) networks are very good at approximating memory-less nonlinear functions, static systems. In the present research predictors based on linear models such as ARX and ARMAX, and nonlinear models, such as FMLPs, have been developed for performing sing-step-ahead (SSP) and multi-step-ahead (MSP) prediction of end-to-end single flow characteristics, flow accumulation, in best-effort networks.

Doddi [23] also adopted a black box approach and predicted one-way end-to-end packet delays of a simulated best-effort network with reasonable accuracy. Doddi [23] used linear models like an Auto Regressive (AR) and an Auto Regressive Moving Average (ARMA) to model delay dynamics of best-effort network. This research also used non-linear identification techniques like an FMLP to model the non-linearities of a network. Use of non-linear identification techniques in predicting end-to-end delay dynamics is also studied by Parlos [24].

Xia et al. [25] used accumulation for developing a congestion control algorithm and gave an indication that accumulation can be a useful quantity for congestion control. Khariwal [26] developed a predictive controller that predicted network packet accumulation and used it as a feedback signal. Khariwal showed that the network accumulation can be a good signal to use for feedback and the research was successful to an extent in improving the QoS in real-time applications. The advantage of choosing accumulation over the end-to-end packet delay is that packet losses or large packet delays do not result in the disruption of the feedback signal. If the end-to-end delay signal is used for feedback purposes, then disruptions will develop whenever a packet is lost or delayed beyond a certain threshold related to application interactivity.

D. Proposed Approach

The objective of the present research is the prediction of end-to-end characteristics of single flow in best-effort networks, using empirical modelling. The present research assumes a best-effort network to be a "black-box", as seen by the source and the destination nodes, while modelling the end-to-end path of a single flows. The User Datagram Protocol (UDP), will be used as the transport protocol, as it is a widely used protocol in media applications.

In present research, the accumulation of end-to-end single flow is chosen as a signal to model end-to-end single flow characteristics. Because of the losses in the network, accumulation signal grows with time and hence, the trend is removed from the accumulation before using it for modelling. As the raw accumulation signal is extremely noisy, the moving average of the accumulation is used for prediction as this smoothes out the noise to some extent.

The Ns-2 [3] simulator has been used to simulate a best-effort network with several intermediate source and destination nodes acting as cross-traffic. Data has been extracted from the traces of ns-2 model and used for creating, validating as well as testing predictive models. Actual traffic data for modelling has been collected from planet-lab [8] network using UPBAT [4]. Data will be collected from different planet-lab nodes to capture various dynamic view of best-effort networks.

Linear identification techniques, such as the AR and the ARMA models, are used in this work for modelling end-to-end single flows. Non-linear identification technique, such as the FMLP, is also used to create non-linear predictive models.

E. Contributions of this Research

The area of modelling the best-effort dynamics is relatively new and very few researchers have attempted to model such systems. Present research makes a bold and honest attempt to develop empirical models for simulated as well as actual traffic data. Contributions of the current research work are as follows:

- Development of empirical predictors for the prediction of end-to-end single flow characteristics in best-effort networks.
- Performance comparison of different linear and non-linear modelling techniques to predict end-to-end single flow characteristics.
- Study the performance of generic empirical predictors for the prediction of end-to-end single flow characteristics in best-effort networks, that are independent of the end-to-end path.

F. Organization of the Thesis

The thesis has been divided in five chapters. Chapter II outlines various system identification techniques for modelling end-to-end flow characteristics. Measurement and analysis of end-to-end flow dynamics is discussed in Chapter III. Prediction results of end-to-end single flow characteristics in a simulated network are presented in Chapter IV. In Chapter V, prediction results of end-to-end single flow characteristics in real best-effort networks are presented. Chapter VI deals with the thesis summary and provides some conclusions. It also includes recommendation for future work in this area.

CHAPTER II

METHODS FOR MODELLING AND PREDICTION OF END-TO-END SINGLE FLOW CHARACTERISTICS

A. Introduction

Estimation problem of the present research is to predict end-to-end single flow characteristics in best-effort networks. An accurate model, which captures important dynamics of a system, is necessary for better prediction of the system. Basically there are two types of models in context of system identification, physical models and empirical models. In physical models, relations between system variables are derived in deductive manner using laws of nature. In empirical models, model is inferred from the observed data of the system. Physical models are simple but very time consuming to derive in most of the cases. Also when dynamics of the system becomes more complex it is unrealistic or impossible to get sufficiently accurate model using physical models. Empirical modelling in these situations is useful for deriving a satisfactory model. The models developed in this research are all empirical models.

System identification (SI) aims to infer a mathematical description of a dynamic system from series of measurements on the system. Identification problem is approached in different way depending upon a priori insight of the system. If no knowledge or only diminutive knowledge about physics of the system is assumed identification process is called "black box" modelling. All models developed in present research are "black box" models i.e. they are exclusively developed on measured data.

The current chapter is organized as follows: At first system identification procedure is explained. It is followed by overview of linear and nonlinear identification methods used in present research. This chapter mainly contains definitions and principles of system identification.

B. System Identification Procedure

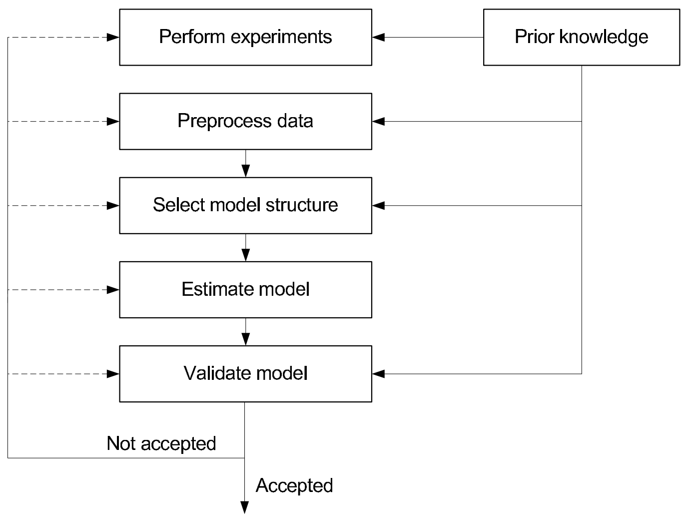


Fig. 1. The Basic System Identification Procedure.

The basic procedure to identify a model of a dynamic system is depicted in the Figure 1 . Naturally, physical insight, prior knowledge of the system and intended use of the model greatly influences all stages of the system identification. A preliminary discussion of each stage is given below:

1. **Experiment**: This is the first and often the most time consuming step of the basic system identification procedure. The experiments should be designed in such a way that they can capture important dynamics of the system. The data-sets thus collected should be analyzed rigorously to make sure that they describe system behavior over its entire range of operation. Some of the main issues in the experiment stage are : design of a suitable input signal and choice of sampling frequency.

2. **Preprocess data**: Pre-processing of the data-sets is often useful to obtain a good model of the system. Data pre-processing includes, e.g., nonlinearity tests, filtering to enhance important frequency ranges, removal of trends and outliers and removal of disturbances, noise, and other undesired effects from the data-sets.

3. **Model structure selection**: Model structures can be classified in two classes,input-output and state space model structures. On a general level the problem of selecting model structure is twofold:

   (a) Select a "family" of model structure to describe the system, e.g., linear model structures, multilayer perceptron networks, wavelets, or Hammerstein models.

   (b) Select a subset of the chosen family of model structures, e.g., an Auto-Regressive Exogenous(ARX) model structure in linear model structures.

   Prior knowledge of the system is useful in selecting an appropriate model structure.

4. **Model parameter estimation**: Once a specific model structure is assumed, the next step is to estimate the parameters in the model structure. Different optimization techniques are available to estimate the model parameters using available data sets. A common method of estimating the parameters is the prediction error approach, where the parameters of the model are chosen so that the difference between the predicted output and the measured output is minimized.

5. **Model validation**: The model developed in previous steps must be evaluated to investigate whether or not it meets the necessary requirements. The model

validity is generally ascertained by testing the model on completely new data sets. The model validation step is closely connected to the intended use of the model.

6. **Going backwards in the procedure**: A path going back from the validation block in Figure 1 indicates that the system identification procedure is executed in an iterative manner. If a developed model does not perform satisfactorily, it is necessary to go back in the procedure to try out various model structures, various optimization techniques, and in the worst case redo the experiment.

Given a finite set of input observations {u(1),....,u(N)} and the corresponding output observations {y(1),....,y(N)}, the aim of the basic system identification procedure is to obtain the free parameters θ and a function $\mathcal{G}()$ such that one-step ahead prediction $\widehat{y}(t|t-1,\theta)$ can be expressed as :

$$\widehat{\mathbf{y}}(t|t-1,\theta) = \mathcal{G}\Big(\phi(t);\theta\Big) \tag{2.1}$$

where, θ is the parameter vector and the ϕ is the regression vector, which contains system inputs u(.), past outputs y(.), or signals derived from the inputs and outputs.

C. Linear Methods

Linear system identification models assume the dynamic relationship between system inputs and outputs to be a linear regression. There are many advantages of developing a linear model:

- Many systems can be described reasonably well by a linear model,
- From a computational perspective it is easy to perform,
- Designing a controller for a linear system is much simpler.

Linear models can be broadly classified into two types, linear input-output models and linear state-space models. In the input-output models, the relationship between the inputs and the outputs is modelled in the form of linear regression. In the state-space models, the system is modelled through intermediate variables called states. Present research uses only input-output model structures as it is very difficult to define states for end-to-end single flow in best effort networks. Moreover, the system under consideration is modelled as a single input single output (SISO) system. Following section briefly describes various linear identification methods used in present research.

1. Auto-Regressive Exogenous Model

The Auto-Regressive Exogenous (ARX) is the simplest and the most used model structure in system identification. The general SISO ARX model can be expressed by the following linear difference equation :

$$y(t) = a_1 y(t-1) + \ldots + a_{n_y} y(t-n_y) + b_1 u(t-n_k) + \ldots + b_{n_u} u(t-n_u-n_k+1) \tag{2.2}$$

where u(t) and y(t) are the input and the output of the SISO ARX model, ny and nu are the number of past outputs and the number of past inputs used in the model, and nk is the pure time delay (the dead time) in the system. The coefficients a1,. . . ,any and b1,. . . ,bnu are known as the model parameters.

From the SISO ARX model represented by the equation 2.2, the following Single Step Predictor (SSP) of the system output can be obtained:

$$\hat{\mathbf{y}}(t|t-1,\theta) = \phi^T(t)\theta \tag{2.3}$$

where, $\varphi(t) = [y(t-1), \ldots, y(t-n_y), u(t-n_k), \ldots, u(t-n_u-n_k+1)]^T$,

$\theta = [a_1, \ldots, a_{n_y}, b_1, \ldots, b_{n_u}]^T$.

The Equation 2.3 is in the form of a linear regression with the model parameter vector θ as the regression vector. The parameter vector θ in the Equation 2.3 is estimated using the least-square method. The least-square method estimates the values of the parameter vector θ that minimizes the mean-square of the prediction error.

The Auto-Regressive (AR) model is the special case of the ARX model where only past values of the output is used for modelling the system. The AR model is also known as time-series modelling. Present research uses the AR model to model an end-to-end single flow characteristics in best effort networks.

2. Auto-Regressive Moving Average Exogenous Model

The Auto-Regressive Moving Average Exogenous Model (ARMAX) is more general input-output model than the ARX model. The AR in the ARMAX model refers to the autoregressive part, and the MA is the moving average and X corresponds to the extra input called the exogenous variable. The ARMAX model is more flexible than the ARX model as it also models disturbance dynamics of the system. The ARMA model formulates the disturbance term as a moving average of a white noise process. The SISO ARMAX model can be represented by the following equation:

$$\begin{gathered} y(t) = a_1 y(t-1) + \ldots + a_{n_y} y(t-n_y) + \\ b_1 u(t-n_k) + \ldots + b_{n_u} u(t-n_u-n_k+1) + \\ c_1 e(t-1) + \ldots + c_{n_e} e(t-n_e) \end{gathered} \tag{2.4}$$

where, ne is the number of past noise terms used in the model, e(t) is the prediction error or residual term, and the other variables are the same as in the ARX model.

The SISO ARMAX predictor can be written as a scalar product between the data vector $\varphi(t+1;\theta)$ and the parameter vector θ:

$$\widehat{\mathbf{y}}(t|t-1,\theta) = \phi^T(t)\theta \tag{2.5}$$

where, $\varphi(t) = [y(t-1),\ldots,y(t-n_y),u(t-n_k),\ldots,u(t-n_u-n_k+1),e(t-1,\theta),e(t-2,\theta),\ldots,e(t-n_e,\theta)]^T$,

θ= $[a_1,\ldots,a_{n_y},b_1,\ldots,b_{n_u},c_1,c_2,\ldots,c_{n_e}]^T$.

The model dependency was indicated by including θ as an argument to ϕ in Equation 2.5. The equation 2.5 is in the form of a pseudo-linear regression and hence the least squares method can be used to solve for θ.

The Auto-Regressive Moving Average (ARMA) model is the special case of the ARMAX model where no input or exogenous variable is used while modelling the system. In present research, the ARMA model is used to predict an end-to-end single flow characteristics in best effort networks.

The system identification toolbox provided by The MathWorks, Inc., is used for linear system identification of an end-to-end single flow characteristics in best effort networks.

D. Neural Network Based Nonlinear Methods

In practice, most systems encountered are non-linear to some extent and in many applications, non-linear models are required to provide acceptable representations. Motivated by this fact, recently there has been much focus on different approaches to nonlinear system identification. Artificial Neural Networks (ANNs) have been shown particularly useful in predicting the dynamics of non-linear systems.

The Multilayer Perceptron (MLP) network is considered as the most-often used member of the neural network family. The main reason of using the MLP network is its ability to model simple as well as very complex functional relationships. The Feedforward Multilayer Perceptron (FMLP) networks are very good at approximating memory-less nonlinear functions. The two-layered feedforward network has the ability to approximate many non-linear function provided the hidden layer contains sufficient nodes.

1. Feedforward Multilayer Perceptron Networks

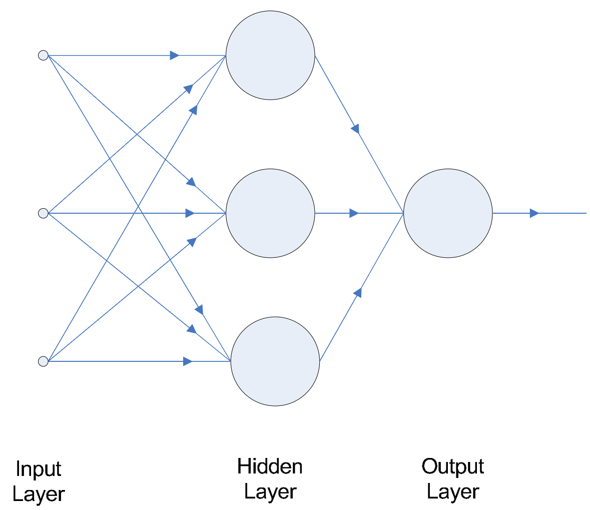


Fig. 2. Schematic Diagram of the Fully Connected FMLP Network.

Figure 2 shows a typical fully connected FMLP network. The FMLP network tries to estimate a non-linear transformation for the input data in order to approximate the output data. The number of input nodes, output nodes and hidden layer nodes depend on the nature and complexity of the system being modelled. In the fully connected FMLP network all units in one layer are connected to all units in the following layer. The mathematical formula expressing the FMLP network takes the form:

$$\hat{\mathbf{y}}(t|t-1;\mathcal{W}) = \mathcal{F}\Big(\mathcal{U}(t-1);\mathcal{W}\Big), \tag{2.6}$$

$\mathcal{F}$ is the nonlinear transformation between the network inputs and outputs, $\mathcal{W}$ is estimated by the learning algorithm. Basically, the learning algorithm adjusts the network weights and the bias terms till the mean square error between the prediction and the observation is less than a prescribed tolerance. A Levenberg-Marquardt method is the standard method for minimization of mean-square error criteria, due to its rapid convergence properties and robustness.

The two layered fully connected FMLP network is used in the present research to predict an end-to-end single flow characteristics in best effort networks. The sigmoidal or the hyperbolic functions are used in the hidden layer nodes while the linear functions are used in the the output layer nodes. The NNSYSID toolbox provided by Magnus Nrgaard, has been used for neural network based system identification of an end-to-end single flow characteristics in best effort networks.

E. Chapter Summary

This chapter gives brief description of the linear methods used for modelling. The linear tools are simple and effective for the linear systems, but fails to model non-linearity in the dynamic systems. The neural network based non-linear methods can be useful for such systems as they can model certain complex systems very effectively. This chapter also introduces neural network based non-linear methods.

CHAPTER III

MEASUREMENT AND ANALYSIS OF END-TO-END SINGLE FLOWS

A. Introduction

The first step for modelling end-to-end single flow characteristics is to obtain sufficient data necessary for developing predictors. To obtain good prediction performance, data-sets used to develop a predictive model should contain important characteristics of the best-effort network. Present research assumes a best-effort network to be a "black-box", as seen by the source and the destination nodes. In such end-to-end network approach, variables only measured at the end points, the source and the destination, are used to model the system. Schematic diagram of end-to-end network measurements is shown in the Figure 3.

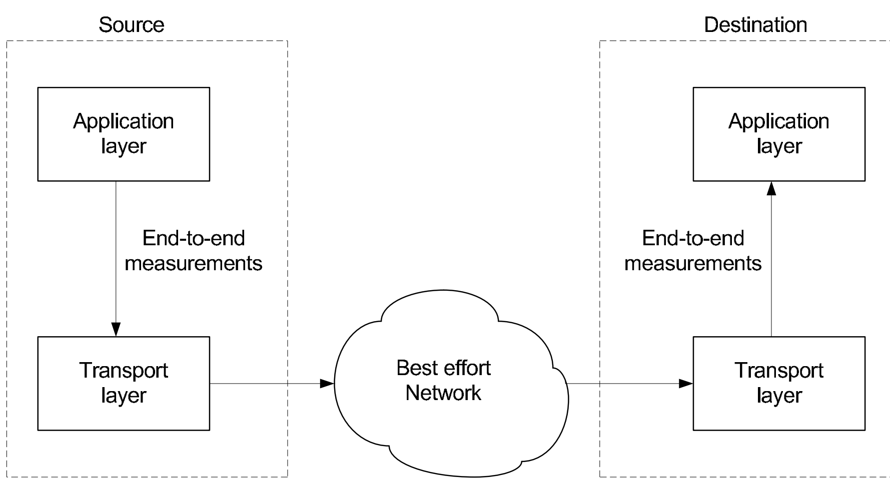


Fig. 3. Schematic Diagram of End-to-End Network Measurements.

B. End-to-End Single Flow Characteristics

Real-time applications, such as audio, requires continuous flow of data from the source to destination. Cumulative amount of data that have been sent into the network by the source at any given instant of time is called send flow. Similarly, cumulative amount of data that have reached the destination at any given instant of time is called arrival flow. When data is sent over the Internet, it is split into segments called data packets. These packets are then directed to their destination by routers over different paths, in general. Once these packets reach their destination, they are reassembled. The time taken by a packet to reach their destination application is called end-to-end delay. Ideally, the end-to-end delay must remain constant over time. In this case, send flow and arrival flow are just time-shifted by the constant delay. Accumulation of a particular flow can be defined as the difference between the cumulative send and arrival flows. For ideal case, that is when end-to-end delay is constant, accumulation should stay constant too.

Due to changing network conditions end-to-end delay does not remain constant. Hence, accumulation in the network also varies with changing network conditions. The dynamic behavior of a best-effort network can be characterized by end-to-end delays, end-to-end delay variation or jitter, packet losses, and throughput measurements of the various flows. These variables have a direct impact on the Quality of Service (QoS) delivered to the users. One of the main reasons for variation in end-to-end delay is the queuing of packets in the network. A packet is said to experience queueing delay as it waits in the queue to be transmitted onto the link. This delay depends on packets that are queued before the specific packet and which are already in the queue waiting to be transmitted. Hence, this delay could vary significantly from one packet to another and it could range from a few milliseconds to hundreds of milliseconds. Since the queue limit or the queue capacity of a router is always finite, incoming packets sometimes do not find place and the router drops these packet. Thus, most of the packet losses in the network occur when the router queues are full. When the packet is queued in the network, accumulation of the network increases. Hence, network accumulation gives direct indiction of the congestion in the network and can be a good signal to gauge present network conditions.

In present research, accumulation of end-to-end single flow is chosen as a signal to model end-to-end single flow characteristics. One way end-to-end delay, the time taken by the packet to travel from the application layer of the source to the application layer of destination, can also be used for modelling end-to-end single flow characteristics. The advantage of choosing network accumulation over the end-to-end delay is that the packet loss or large packet delays do not result in the disruption of the signal. Also network accumulation signal could be used during instances of flow reversal when packet arrive at their destination out-of-order. When the packet drop occurs in the network, the lost packet never reaches destination. Because of this, accumulation signal which is the difference of send and arrival flow, grows. That means the accumulation signal are made up of two components : total losses occurred in the network and accumulation at the present time. Because of these losses in the network, accumulation signal grows with time and hence, the trend is removed from the accumulation before using it for modelling. As the raw accumulation signal is extremely noisy, the moving average of the accumulation is used for prediction as this smoothes out the noise to some extent.

C. Collection of Simulated Data

This section describes the generation of artificial or simulated UDP traces in ns-2. Ns-2 generated data will now be called as simulated data. This section also contains assumptions, details of network topology and brief analysis of simulated data.

1. Assumptions

The major assumptions made during the collection of simulated data are:

1. A single flow travels on a unique path between a source and a destination. Hence, flow reversal is not considered in the predictor development process.

2. Packets having more than 150 milliseconds one way end-to-end delay are considered as lost packets. This assumption is necessary because in real time applications late arrived packets are as good as being lost in the network.

2. Network Architecture

A simulated network must be designed in such a fashion that the simulated data contains important characteristics of the best effort network. The Ns-2 simulator is used to simulate best-effort network with several intermediate source and destination nodes acting as cross-traffic. The network simulated in present research is normalized and used only to demonstrate the prediction performance of end-to-end single flows.

The simulated network parameters are tuned to reflect certain important characteristics of the best effort network. For example, the ratio of the end-to-end flow to that of the total cross-traffic flow is kept less than 1%. A traffic mix of Transport Control Protocol(TCP) based flows and UDP based flows is approximately maintained as 90% and 10% respectively. About 82% of the total network traffic is kept as hypertext transfer protocol (HTTP) traffic to make simulated network comparable with the Internet. Simulated cross-traffic is suddenly increased and decreased to mimic bursty nature of the cross-traffic in the actual best effort networks. Simulation conditions are also tuned to enable some matching of the end-to-end delay profiles with actual traffic data. Figure 4 shows the basic topology of the simulated network.

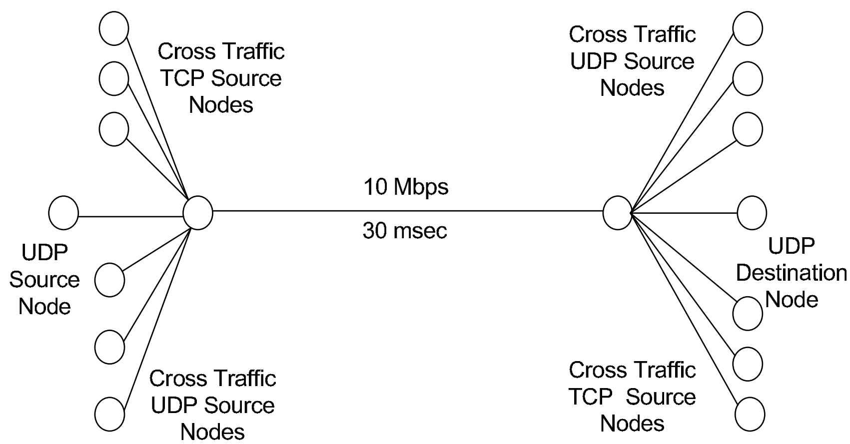


Fig. 4. Network Topology for Simulated Data.

The simulated network has 230 TCP nodes and 10 UDP nodes. Every node in the network behaves as a flow source or a flow sink. Each TCP source sends either ftp or http flow in the network. Ftp and http flow creates variable bit rate traffic in the network. The UDP source sends constant bit rate (CBR) traffic in to the network. The nominal packet size of the CBR traffic is 256 bytes and the nominal inter-departure time is 25 milliseconds (ms). Two UDP nodes, the source and the destination, are used as a flow source and a flow sink of an end-to-end single flow being modelled in present research.

The bottleneck link, the most congested link in the network, has a bandwidth of 10 mbps and a propagation delay of 30 ms. All links and queues are chosen to be duplex and drop-tail, respectively. The simulation is performed for 100 seconds.

The data sets have been generated for 20 ms and 60 ms inter-departure time of the send packets: Different traces have been obtained by varying the source send-rate between 10 Kbps to 60 Kbps for each inter-departure time. Here, source rate is varied by keeping the packet inter-departure time constant and varying the packet-size of the sent packets. It is important to note that the inter-departure time and the packet-size of the sent flow are constant for a particular session. The Data is then extracted from the traces of ns-2 model and used for creating, validating as well as testing predictive models.

3. Analysis and Pre-Processing of the Simulated Data

Present research aims to create predictive models for the accumulation of the end-to-end single flow in best-effort networks. The accumulation is computed by measuring the cumulative send and arrival flow periodically at the source and the destination. After lots of experiments the time interval for measuring the cumulative flows is kept equal to the inter-departure time of send packets. As discussed in the earlier section, the accumulation is a growing signal and so the trend has been removed from it before using for modelling. Here, the trend is dynamically calculated by adding mean slope of last 1 second window to the current value of the trend. As the accumulation is extremely noisy, the moving average of the accumulation is used for prediction as this smoothes out the noise to some extent. The moving average window is set as 120 ms and the window is moved by one sample i.e. window is moved by 20 ms if the sampling time is 20 ms and 60 ms if the sampling time is 60 ms.

A preliminary study on autocorrelation functions of moving average accumulation is necessary as it helps in choosing the order of the linear predictive models. Figure 5 represents the typical normalized auto-correlation of the accumulation in the simulated best-effort networks. It can be seen from the figure that even after 500 lags the auto-correlation drops only to 0.83, which shows that the data sets have long-term dependency of very high order. The direct practical implication of the long-term dependency is that it is difficult to obtain an empirical model for these data.

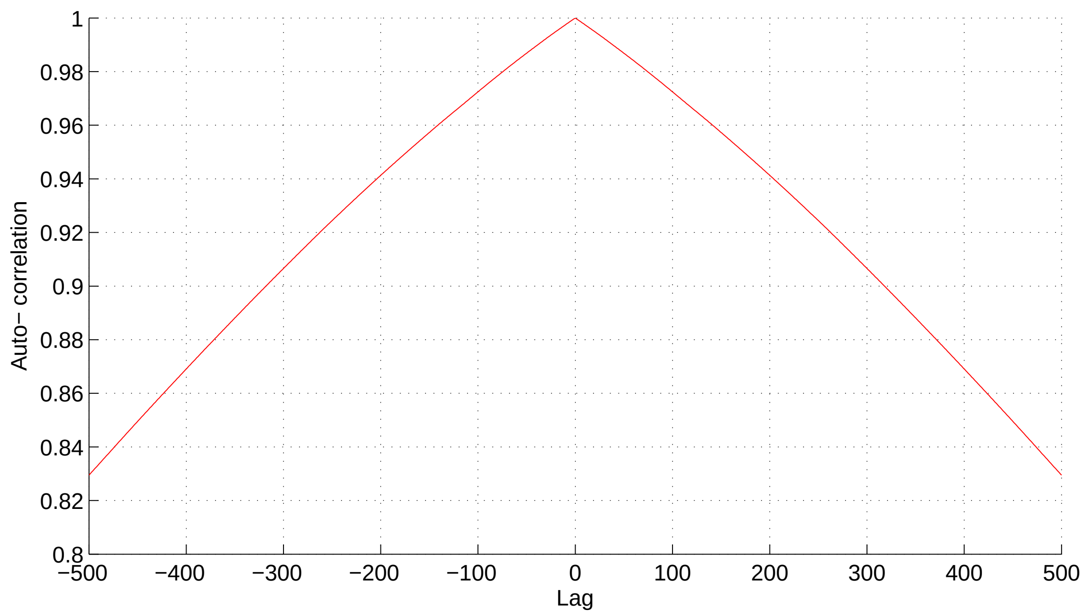


Fig. 5. Auto-Correlation Function of Moving Average Accumulation for 500 lags.

D. Collection of Actual Traffic Data

Although many simulators are available, none of them can accurately capture precise behavior of the best-effort networks mainly due to the complexity and non-equilibrium involved. Therefore, It is important to check the performance of the proposed approach on real data. This section describes the collection of end-to-end single UDP flow data on the planet-lab network using the UPBAT tool. The data thus collected will now be called as "actual traffic data". This section also contains assumptions, information about experimental setup and brief analysis of actual UDP traffic data.

1. Assumptions

The most important assumption in the collection of the real UDP flow data is that the packets having more than 150 milliseconds one way end-to-end delay are considered as lost in the network. This assumption is important because in real-time applications late arrival of the packet is equivalent to losing that packet in the network.

2. Experiment Setup

Figure 6 shows the basic topology used for measuring the actual UDP traffic data on the PlanetLab network. The UDP Packet Behavior Analyzing Tool (UPBAT) tool developed by Yeom [4] has been used in the present research for measuring one-way end-to-end single UDP flow characteristics. The UPBAT tool requires access to two nodes, a source node and a destination node, to collect end-to-end single flow UDP data. In the present research, one-way end-to-end flow characteristics are collected from various nodes on the PlanetLab network. PlanetLab is a network of computers strategically located at sites around the world, forming a test-bed or platform for conducting Internet scale experiments and for developing new network services. Network services deployed on the Planet-lab experience all behavior of the real Internet and hence, create a unique environment to conduct experiments at Internet scale.

The UPBAT tool uses two separate threads for sending and receiving UDP data packets. A server program is started on the destination node and a client program is started on the source node. Packets are sent from the source node to the destination node and after reaching the destination node they are echoed back to the source node.

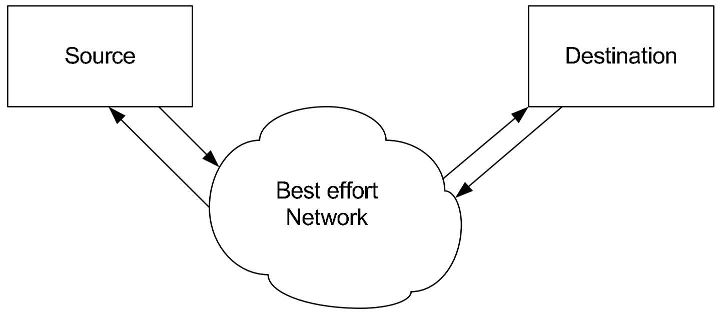


Fig. 6. Network Setup for Measured Traffic Data Collection.

When packets finally reach back to the source both forward and reverse delays for UDP packets are calculated.

Different data-sets are collected by varying the source send-rate between 20 Kbps to 50 Kbps. Various data-sets are also collected at different times of the day to capture variability of the cross-traffic in the best-effort networks. Data is also collected from three different end-to-end node pairs on the Planetlab to capture various dynamic view of the best-effort networks. The data sets have been collected for 20 ms and 60 ms inter-departure time of the send packets. It is important to note that the inter-departure time and the packet-size of the sent flow are kept constant for a particular session.

3. Analysis and Pre-Processing of the Real Data

The UPBAT tool gets both forward and reverse delays for UDP packets and thereby allows one to obtain end-to-end single flow accumulation as a function of time using several parameters like the packet size and inter-departure time. The accumulation signal is then detrended to account for the losses in the network. The next step is to apply the principle of moving average window to the accumulation signal. The moving average window principle is based on computing the average of the data in a particular time interval and then moving this window forward in small time steps. Thus moving average accumulation of end-to-end single flow signal is used for prediction purposes. Here, the trend is dynamically calculated by adding mean slope of last 1 second window to the current value of the trend. The moving average window is set as 120 ms and the window is moved by one sample i.e. window is moved by 20 ms if the sampling time is 20 ms and 60 ms if the sampling time is 60 ms.

Figure 7 represents the typical normalized auto-correlation of the moving average accumulation of the end-to-end single flow for the real-data. It can be seen from the figure that even after 500 lags the auto-correlation drops only to 0.87, which shows that the data sets have long-term dependency of very high order.

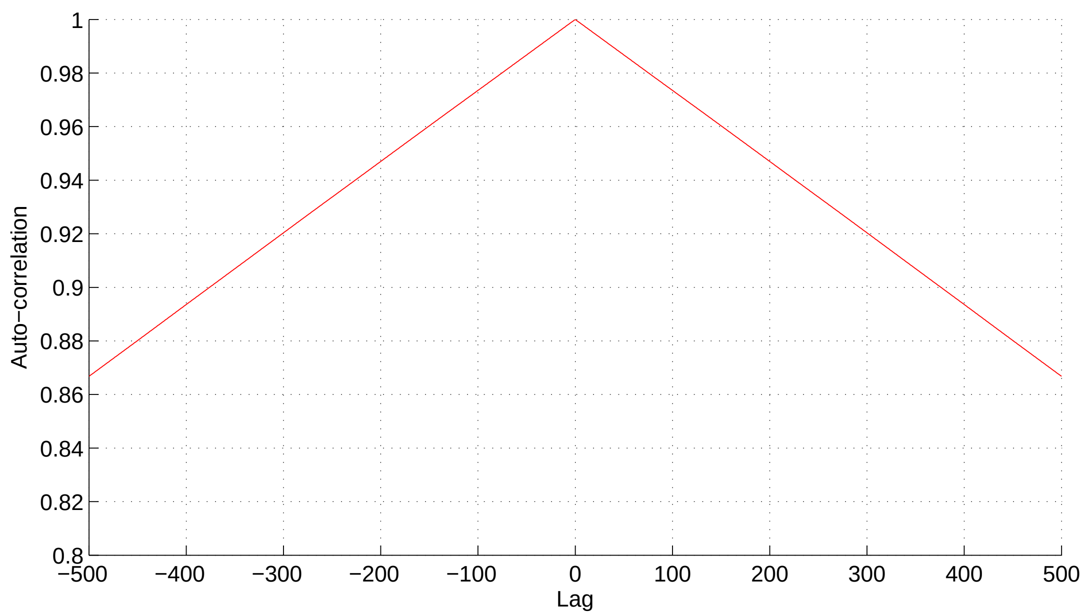


Fig. 7. Auto-Correlation Function of Moving Average Accumulation for 500 lags; UDP Trace Collected Between TAMU and Seattle3 at a Constant Send Rate of 50 Kbps.

E. Chapter Overview

This chapter describes data collection process for simulated traffic data as well as measured traffic data. A brief discussion of various available end-to-end flow characteristics is also given. Important assumptions in the data collection process are also stated in this chapter. Brief analysis of the collected data sets is also given.

CHAPTER IV

END-TO-END SINGLE FLOW PREDICTION FOR SIMULATED TRAFFIC DATA

A. Introduction

For any complex effort, good engineering practice suggests that the effectiveness of the proposed approach should be evaluated for simulated conditions before testing it on real world conditions. This chapter investigates the performance of various empirical models for predicting end-to-end single flow characteristics in a simulated best-effort network. The empirical models have been developed using the linear and non-linear empirical techniques described in Chapter II. Next section describes the performance metrics used in this research. It is followed by a section that gives description of training and validation data sets. The following section explains development of the linear and non-linear predictors. The subsequent sections then deal extensively with a comparative study of the various linear and nonlinear predictive models.

B. Performance Metrics

In this research, Mean Square Error(MSE) is used as a performance metric for the predictors developed. It is defined as the ratio between the sum of the square of the prediction error and the sum of the square of the input data. MSE can be represented by the following equation:

$$MSE = \frac{\sum_{k=1}^{N} \left(x(k) - \widehat{x}(k|k-1)\right)^2}{\sum_{k=1}^{N} x(k)^2} \times 100 \tag{4.1}$$

where N is the total number of data points, $x(k)$ is the actual value of the output, and $\widehat{x}(k|k-1)$ is the prediction value of the output. MSE can be also defined as the inverse of *Signal-To-Noise Ratio*(SNR). MSE considered as one of the best performance metric that gives a good picture on the quality of the predictor.

C. Description of Training and Validation Data Sets

The data-sets have been extracted from the ns-2 traces for developing and validating predictive models. Selection of training, testing and validation data sets is closely connected to the intended use of the model. Main motivation of the current research is to develop an accurate predictor that can be used as a input to a controller that controls the sending rate of packets over the networks in real-time. The source rate of the end-to-end flow can be varied in two ways, by varying the packet inter-departure time or by varying the packet-size. After various experiments, it is observed that when the inter-departure time of the send packets was changed the end-to-end flow characteristics reflected in the data-sets is also changed drastically. Hence, empirical models developed for data-set having one packet inter-departure time performed extremely bad for the data-sets having different inter-departure time of the send packets. Therefore, two different sets of linear and non-linear predictors are developed and tested at each 20 ms and 60 ms inter-departure time of the send packets. The predictive models are trained at a 30 Kbps source send-rate for each inter-departure time. Performance of the developed models is then evaluated by varying source send-rate between 10 Kbps to 60 Kbps. Here, source send-rate is varied by changing the packet-size of send packets. It is important to note that the inter-departure time and the packet-size of the sent flow are constant for a particular session. The simulation is performed for 100 seconds in all cases.

The network accumulation for each traces is computed by periodically calculating the cumulative send and arrival flow at the source and the destination. The time interval for measuring cumulative flows is equal to the inter-departure time of send packets. The data-sets is then processed before using for modeling and testing of the predictive models. Processing of the data-sets includes two steps. At first, the trend is removed from the accumulation to calculate present accumulation in the network. And then moving average accumulation is calculated for system identification purpose. Here, the trend is dynamically calculated by adding mean slope of last 1 second window to the current value of the trend. The moving average window is set as 120 ms and the window is moved by one sample i.e. window is moved by 20 ms if the sampling time is 20 ms and 60 ms if the sampling time is 60 ms.

D. Development of Linear and Non-linear Predictors

The next step is to use system identification techniques to obtain the best empirical model. The training data is divided into three sets namely training data, testing and validation data as shown in Figure 8. The predictors are developed on the training data and testing data and then they are evaluated on a validation data which is part of the data-set but not used in the estimation of the weights. Here, different sets of linear and non-linear predictors are developed and tested for 20 ms and 60 ms packet inter-departure time of the send packets.

After various permutations and combinations, an AR predictor with model of the order {41} and ARMA with model order {42 16} are found give the best fit for the training data-set having 20 ms inter-departure time of the send packets. This means that 41 past outputs have been used in the AR model and 42 past outputs and 16 past noise terms have been used in the ARMA model. The model order is very high in this case which indicates the long term dependency of the data-sets. For the

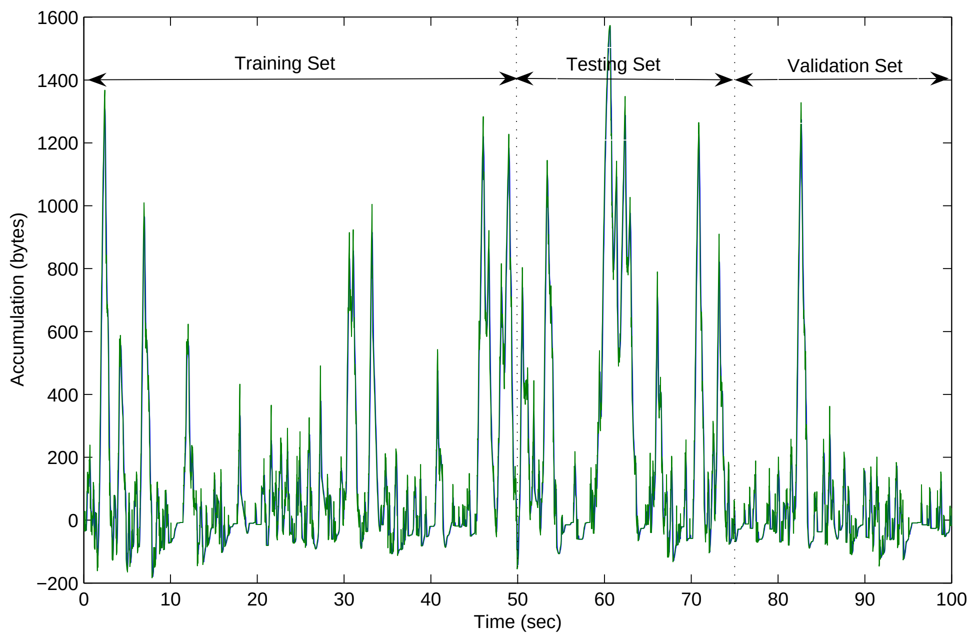


Fig. 8. Representation of Training, Testing and Validation Data Sets.

data-sets having 60 ms inter-departure time of the send packets, an AR predictor with model structure {26} and ARMA with model structure {26 8} are found to be most suitable for the prediction. There are no inputs for the predictors as the cross-traffic, which has the highest impact on the flow characteristics, cannot be measured and it is considered as a disturbance of the model.

Training method of non-linear predictor is completely different from the linear models. Selecting model-structure and parameters of non-linear model is very time consuming and effort taking process. After extensive search over several possible FMLP architectures, FMLP model structure {35 4 1} which translates into 35 input layer nodes, 4 hidden layer nodes and 1 output layer is found to be the best model-structure for the training data-sets having 20 ms inter-departure time of the send packets. Similarly, for the training data-set having 60 ms packet inter-departure time, most suitable FMLP model structure is {21 3 1}. During the training process the performance of the predictor is determined using the mean square error of the signal. Here, it can be noted that the model orders of the training data-set having 20 ms packet inter-departure time is much higher than model orders of the training data-sets having 60 ms packet inter-departure time. Hence, it can be concluded that the order of the model structure is reduced when the inter-departure time of send packet is increased.

E. Single-Step-Ahead Prediction

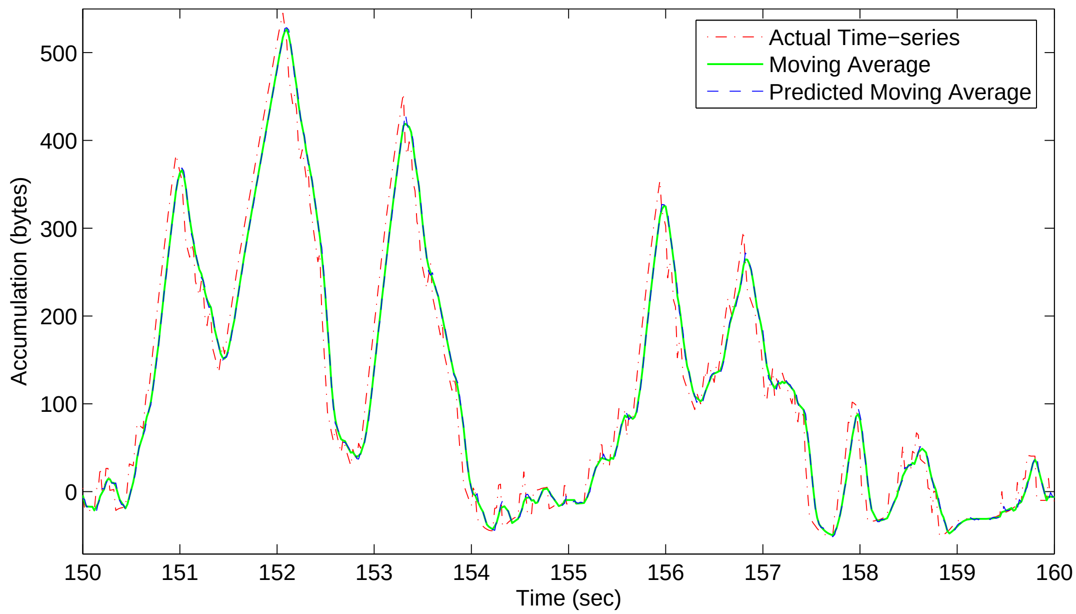
A single step-ahead prediction is a first step in evaluating the performance of the developed predictor. SSP in following cases means 20 ms ahead prediction for the data-sets having 20 ms inter-departure time of the send packets and 60 ms ahead prediction for the data-sets having 60 ms inter-departure time of the send packets.

1. Performance Evaluation of Single-Step-Ahead Predictors

Performance evaluation of the trained linear and non-linear predictors is presented in this section. This is done by testing each of these models for different source send-rate test cases.

Figure 9 shows the SSP of moving average accumulation using the AR model. It depicts the actual accumulation, the moving average accumulation and the predicted moving average accumulation for a constant send rate of 20 Kbps with 20 ms inter-departure time of the send packets. It also shows the errors between the predicted moving average accumulation and the original accumulation as well as the errors between the predicted moving average accumulation and the moving average flow accumulation. The figure shows the predictor can capture the dynamics of the network for one-step ahead prediction. It should be noted that the maximum prediction error with actual accumulation is 50 bytes. Similarly, Figure 10 shows the SSP of moving average flow accumulation using the ARMA model for a constant send rate of 10 Kbps with 20 ms inter-departure time of the send packets. Figure 11 shows the SSP of moving average flow accumulation using the FMLP model for a constant send rate of 30 Kbps with 60 ms inter-departure time of the send packets.

For the sake of clarity of presented results only 500-1000 samples have been shown in all the figures. It can been seen in the figures that predictors perform bad during sudden increase and decrease of the accumulation. As can been seen from Figures 9, 10, 11 that AR, ARMA perform almost similar to each other for the SSP of moving average as well as actual accumulation. All the figures also indicate that the developed models are reasonably accurate for the single step-ahead prediction of actual accumulation.



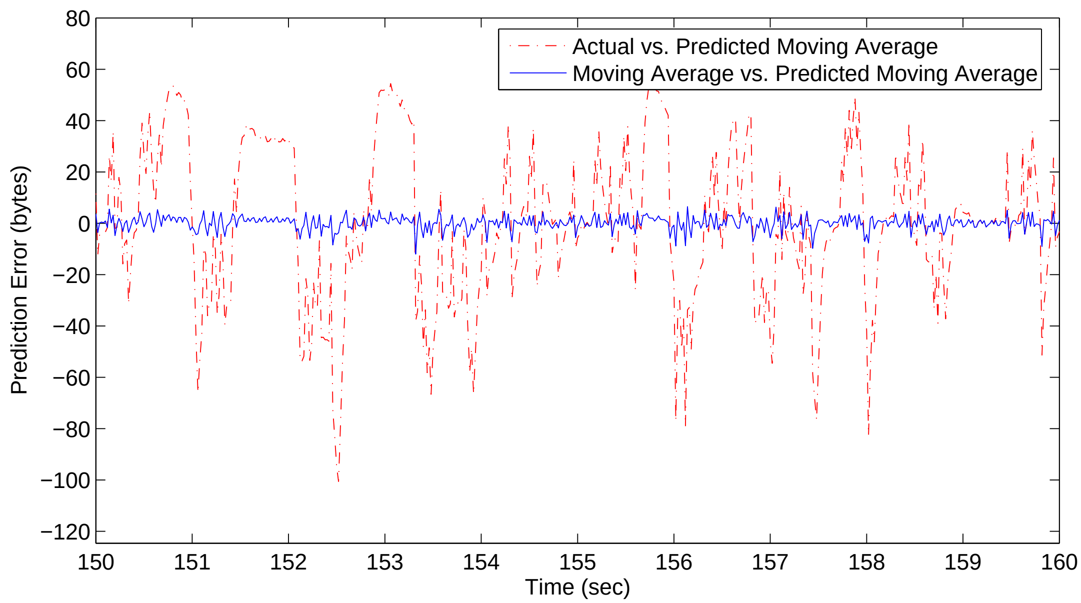


Fig. 9. Single-Step-Ahead Prediction of Moving Average Accumulation Using the AR Model; Constant Send Rate of 20 Kbps with 20 ms Inter-departure Time of the Send Packets.

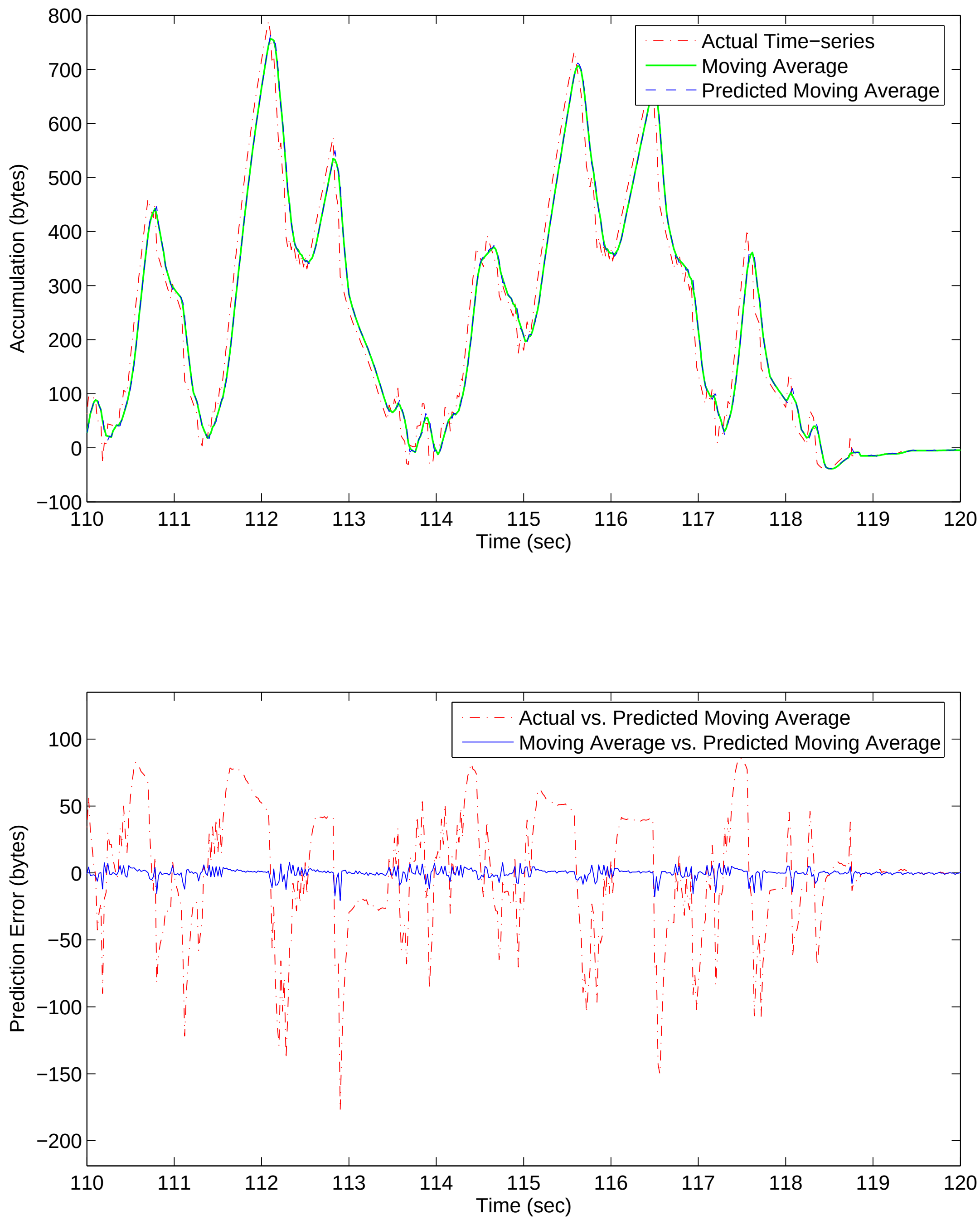


Fig. 10. Single-Step-Ahead Prediction of Moving Average Accumulation Using the ARMA Model; Constant Send Rate of 10 Kbps with 20 ms Inter-departure Time of the Send Packets.

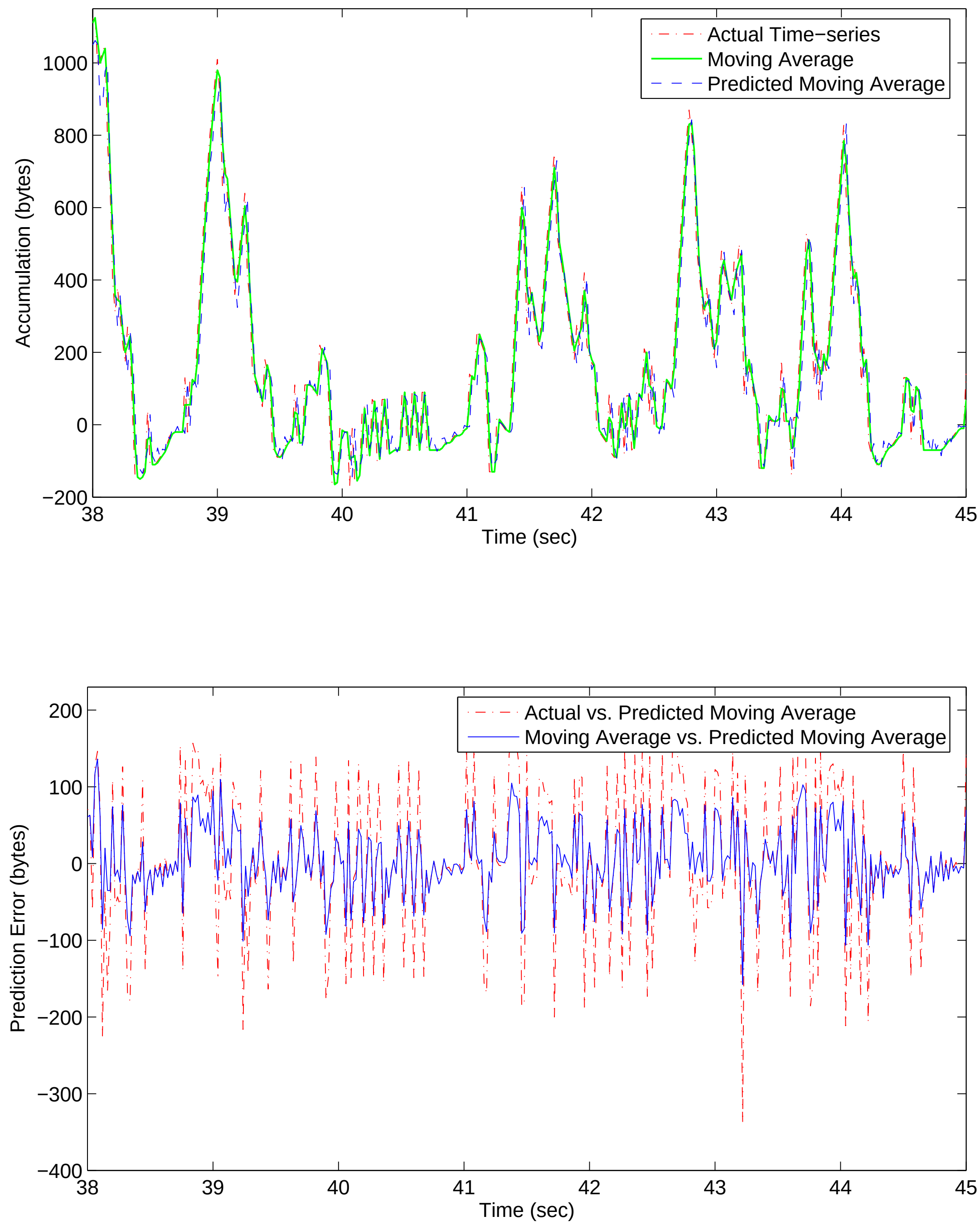


Fig. 11. Single-Step-Ahead Prediction of Moving Average Accumulation Using the FMLP Model; Constant Send Rate of 30 Kbps with 60 ms Inter-departure Time of the Send Packets.

2. Comparison of Single-Step-Ahead Predictor Performance

The results of the SSP on all the test cases using AR, ARMA and FMLP are tabulated in this section. Tables I and II show the performance evaluation results of the AR, ARMA and FMLP predictor on the various send rate test cases in terms of the performance indicator MSE. It can be seen from Table I that AR, ARMA and FMLP results are consistent for various send rate cases having 20 ms inter-departure time of send packets. Table II shows the SSP results of the AR, ARMA and FMLP predictor for the various send rate cases having 60 ms inter-departure of the send packets. Table II shows that the AR and ARMA model perform equivalent while the FMLP model performs slightly inferior for certain send rate cases.

The results of tables I and II can't be compared because Table I represents 20 ms ahead prediction and Table II represents 60 ms ahead prediction.

From the Tables I and II, it can be concluded that the developed linear and non-linear predictors gives satisfactory single-step ahead prediction results for different source send-rate cases.

Table I. Comparative MSE Results of Single-Step-Ahead Predictions for Send Rate Test Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR	ARMA	FMLP
10Kbps	1.32	1.33	1.36
20Kbps	1.01	1.03	1.04
40Kbps	0.73	0.73	0.76
50Kbps	1.53	1.55	1.56
60Kbps	1.12	1.16	1.25

Table II. Comparative MSE Results of Single-Step-Ahead Predictions for Send Rate Test Cases Having 60 ms Packet Inter-departure Time.

send rate	AR	ARMA	FMLP
10Kbps	3.54	3.47	3.60
20Kbps	4.89	4.91	4.97
40Kbps	4.03	4.04	4.42
50Kbps	5.26	5.23	7.65
60Kbps	4.02	4.08	5.15

F. Multi-Step-Ahead Prediction

The present section explores multi-step-ahead prediction performance of the developed linear and non-linear predictors.

1. Performance Evaluation of Multi-Step-Ahead Predictors

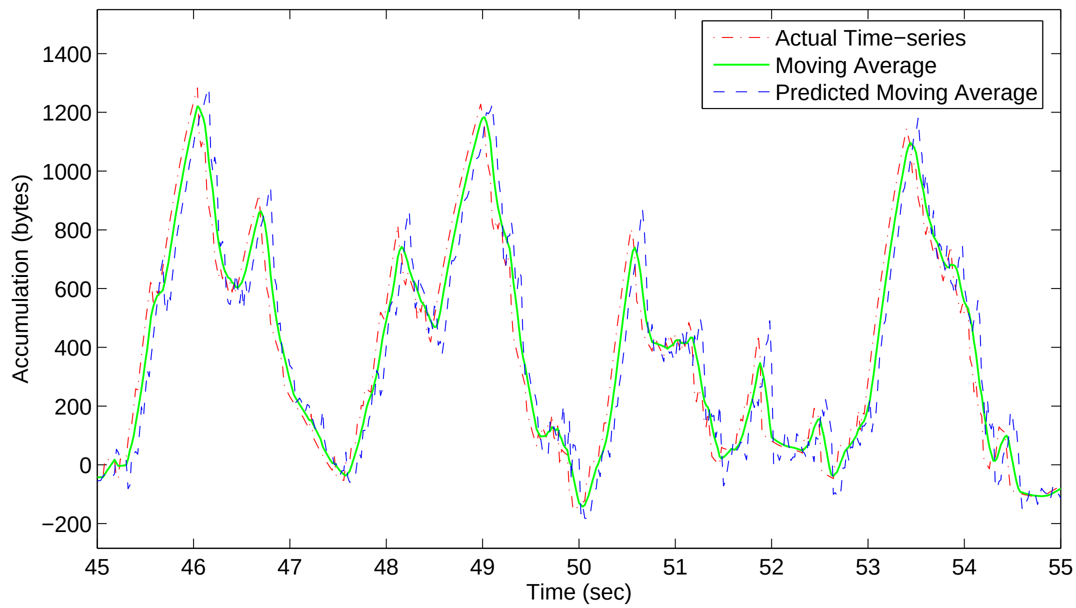
The send-rate test cases used for evaluating the MSP predictors are same as the send-rate cases used for evaluating SSP predictors. This will be helpful in comparing various time-step-ahead predictors on a common scale. Multi-step ahead prediction contains three sections: 120 ms-ahead prediction, 240-ms ahead prediction and 420 ms-ahead prediction. The motivation for selecting certain time-ahead prediction instead of number of steps ahead prediction is to examine the effect of packet inter-departure time on the prediction performance. With certain time ahead prediction, it becomes easier to compare prediction results for data-sets having 20 ms and 60 inter-departure time of send packets.

a. 120 ms-Ahead Prediction

For the end-to-end single flows having 60 ms inter-departure time of send packets, 120 ms-ahead prediction means two step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of send packets, it means six step-ahead prediction.

Figure 12 shows the 120 ms-ahead prediction of moving average accumulation using the AR model. It depicts the actual accumulation, the moving average accumulation and the predicted moving average accumulation for a constant send rate of 40 Kbps having 20 ms inter-departure time of the send packets. It shows a good 120 ms-ahead prediction and the MSE for this case is 2.67%. Though MSE is good for this prediction, time-shift between the predicted moving average accumulation and the actual accumulation can be easily observed. It should be observed that the maximum prediction error between the predicted moving average and the actual accumulation is 400 bytes.

Figure 13 shows the 120 ms-ahead of moving average flow accumulation using the ARMA model for a constant send rate of 10 Kbps having 60 ms packet inter-departure time. The MSE for the test case shown in the figure is 7.91%. Comparison of the Figure 12 and 13 shows that the prediction errors are higher in cases of the end-to-end single flows having 60 ms inter-departure time of the send packets. Figure 14 shows the 120 ms-ahead prediction of moving average accumulation using the FMLP model for a constant send rate of 50 Kbps having 20 ms inter-departure time of the send packets. It shows a reasonably good prediction and the MSE for this test case is 5.83%.



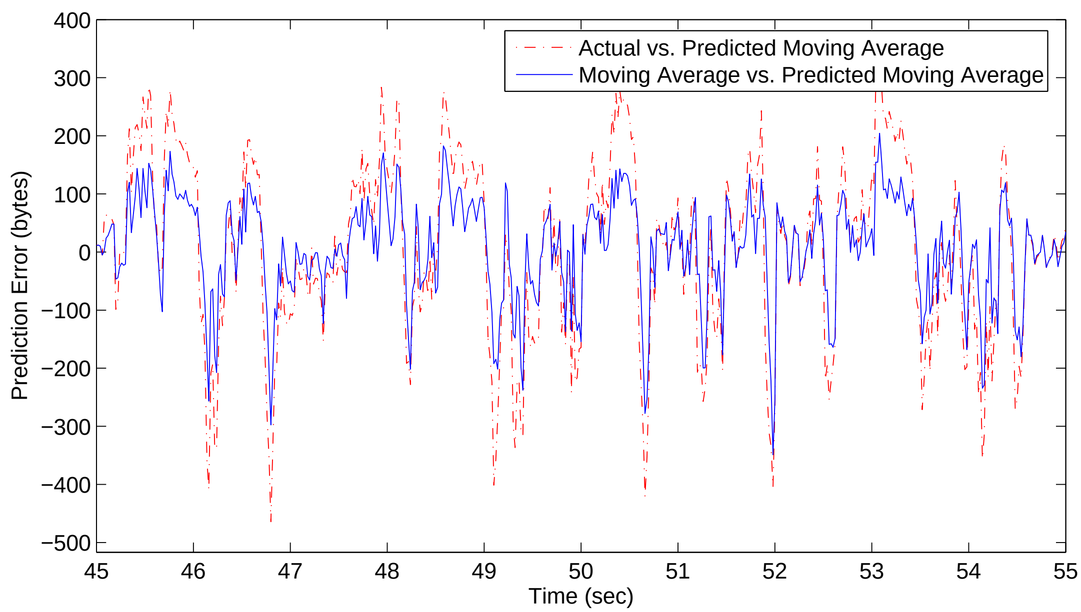
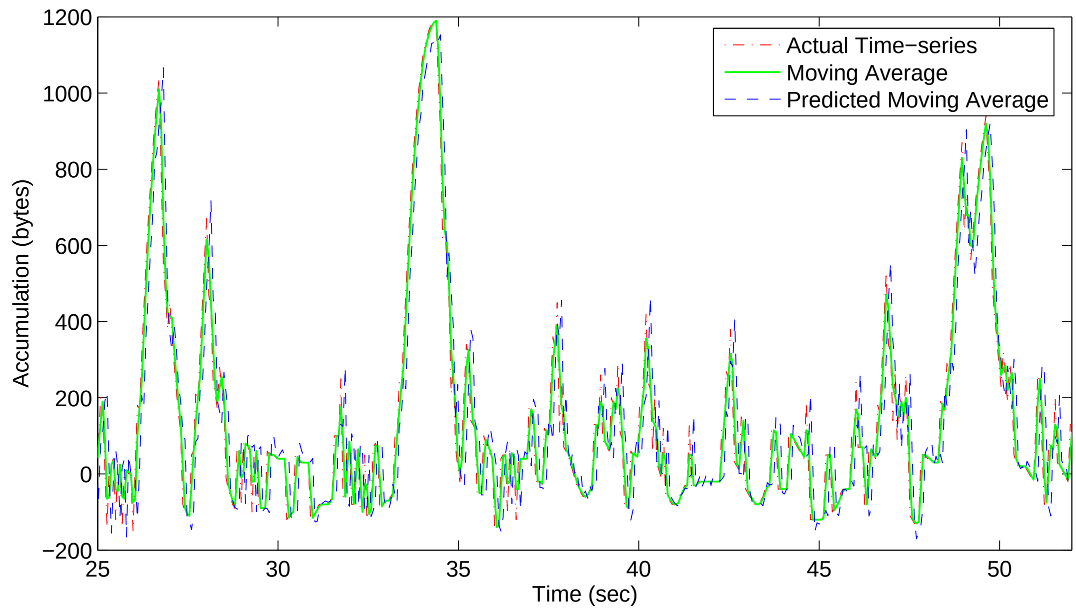


Fig. 12. 120 ms-Ahead Prediction of Moving Average Accumulation Using the AR Model; Constant Send Rate of 40 Kbps with 20 ms Inter-departure Time of the Send Packets.



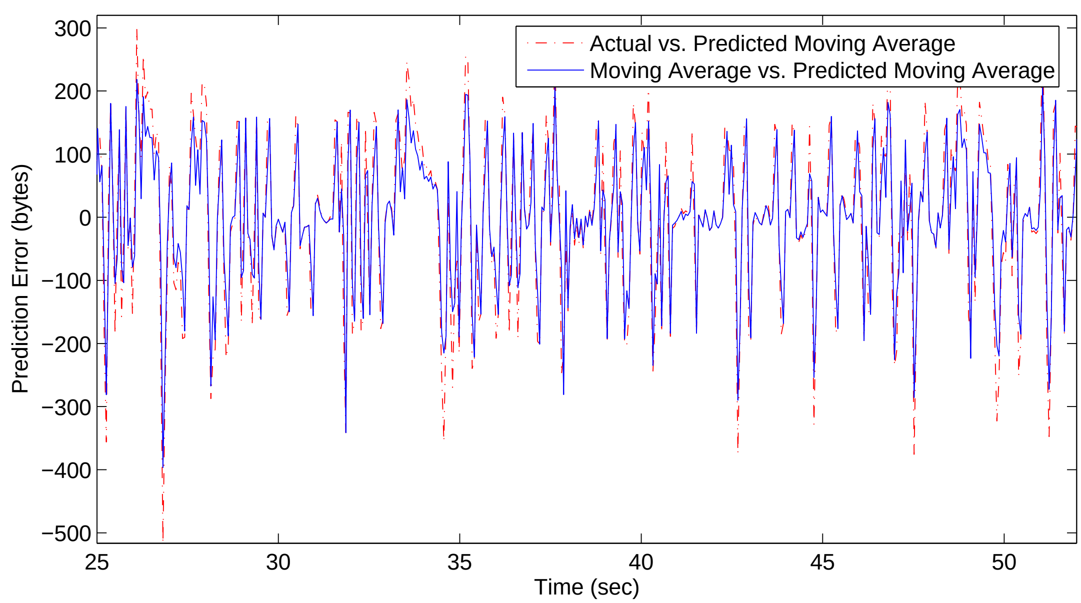


Fig. 13. 120 ms-Ahead Prediction of Moving Average Accumulation Using the ARMA Model; Constant Send Rate of 10 Kbps with 60 ms Inter-departure Time of the Send Packets.

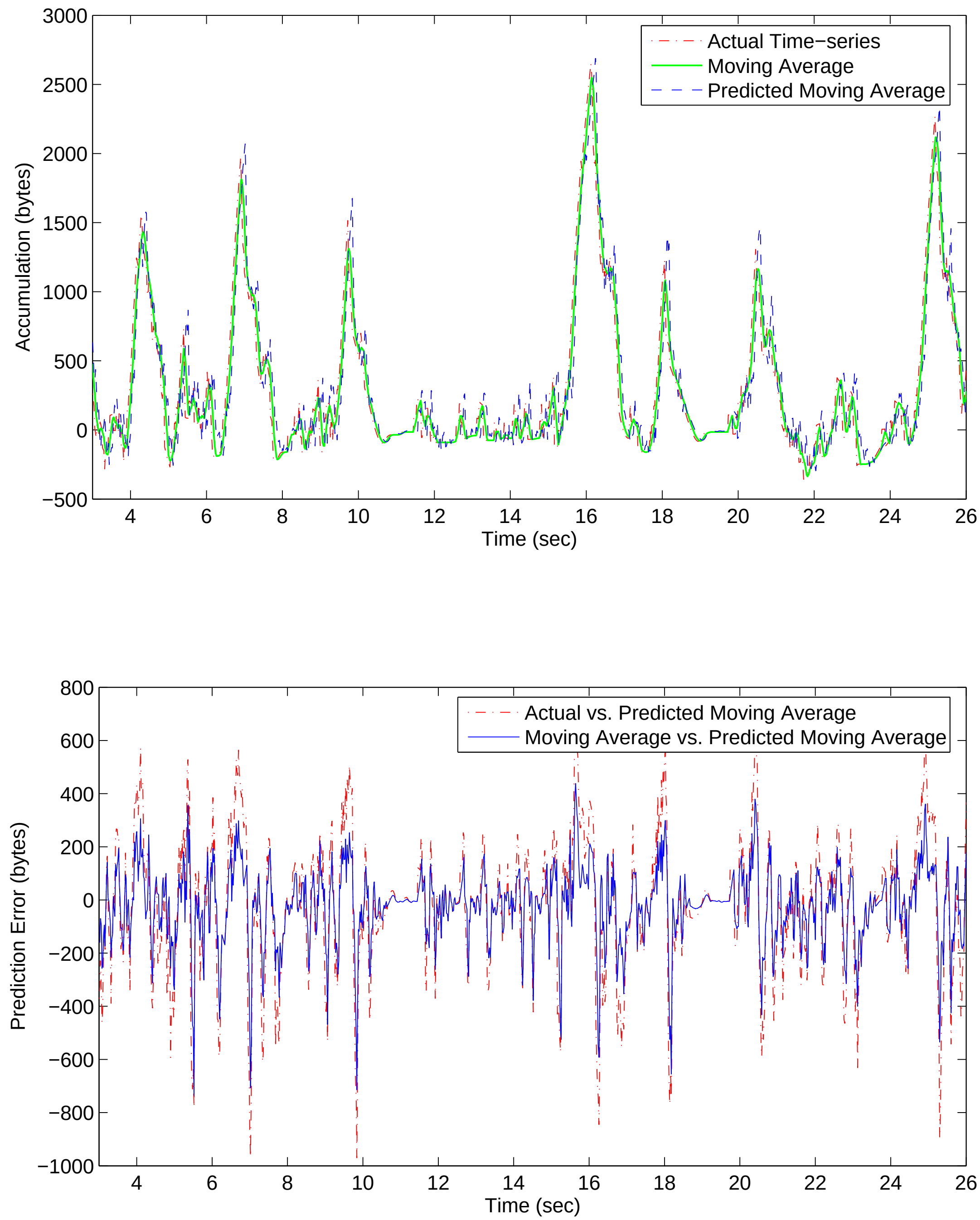


Fig. 14. 120 ms Ahead Prediction of Moving Average Accumulation Using the FMLP Model; Constant Send Rate of 50 Kbps with 20 ms Inter-departure Time of the Send Packets.

b. 240 ms-Ahead Prediction

For the end-to-end single flows having 60 ms inter-departure time of the send packets, 240 ms ahead prediction means four step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of the send packets, it means twelve step-ahead prediction.

Figure 15 shows 240 ms-ahead prediction of moving average accumulation using the AR model. It shows 240 ms-ahead prediction for a constant send rate of 30 Kbps having 20 ms inter-departure time of the send packets. It shows that fairly good 240 ms-ahead prediction can be achieved for end-to-end single flows having 20 ms inter-departure time of the send packets. It should be observed that the maximum prediction error between the predicted moving average and the actual accumulation is 1000 bytes. Figure 15 also shows the increase of time-shift between the predicted moving average accumulation and the actual accumulation. This time-shift is an important factor because timeliness of the prediction is as important as the accuracy because of the intended use of the predictor.

Figure 16 shows the 240 ms ahead prediction of moving average flow accumulation using the ARMA model. It shows 240 ms-ahead prediction for a constant send rate of 50 Kbps having 20 ms packet inter-departure time. It shows a reasonably good prediction and although prediction errors are high, the developed ARMA model can capture some important flow dynamics. Figure 17 shows the 240 ms-ahead prediction of moving average accumulation using the FMLP model for a constant send rate of 40 Kbps having 60 ms inter-departure time of the send packets. The MSE for this test case is 25.66%. Figure 17 shows that FMLP does not perform well for 240 ms ahead prediction for end-to-end single flow having 60 ms packet inter-departure time. A big time-shift and missing of some spikes can also be easily observed.

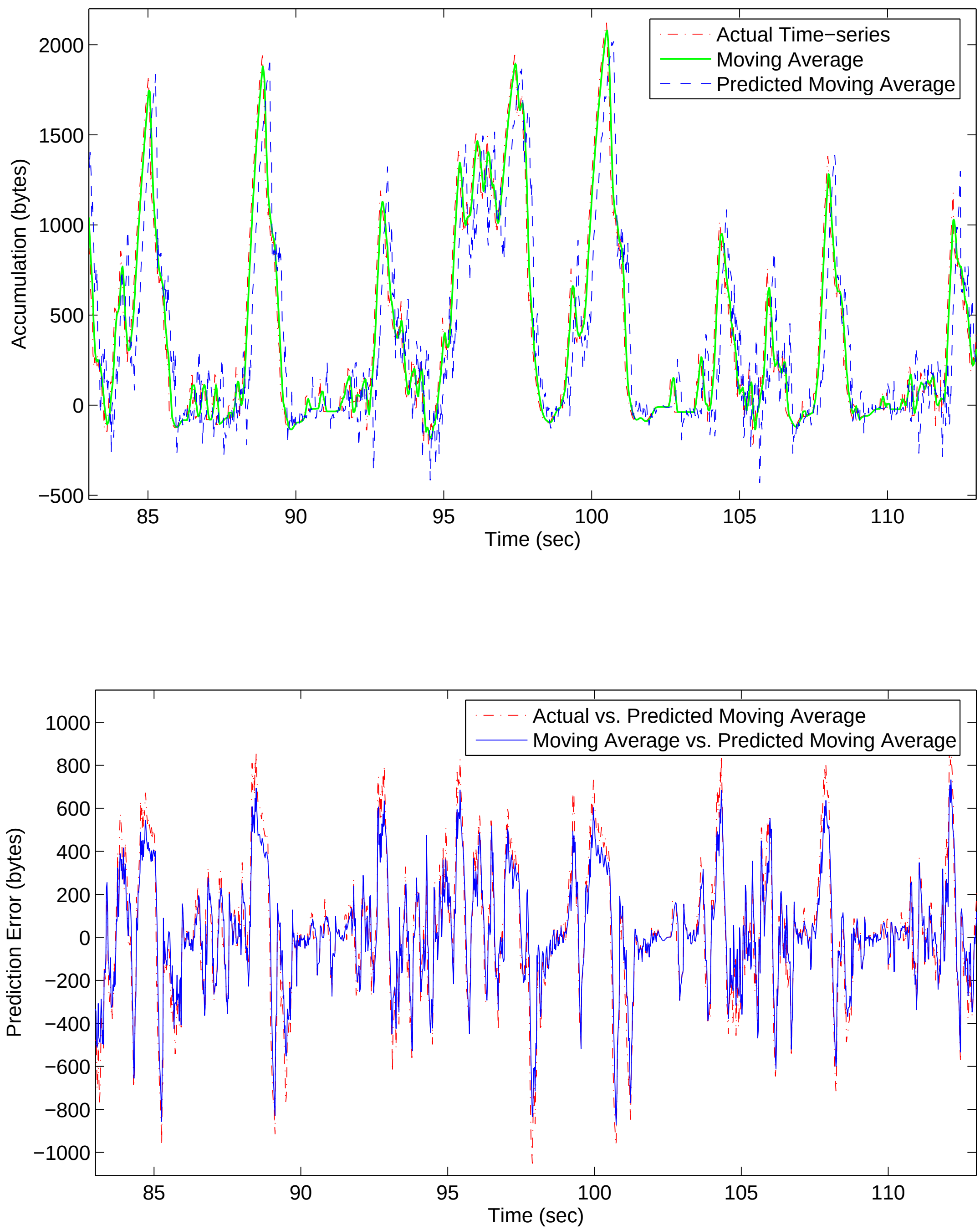
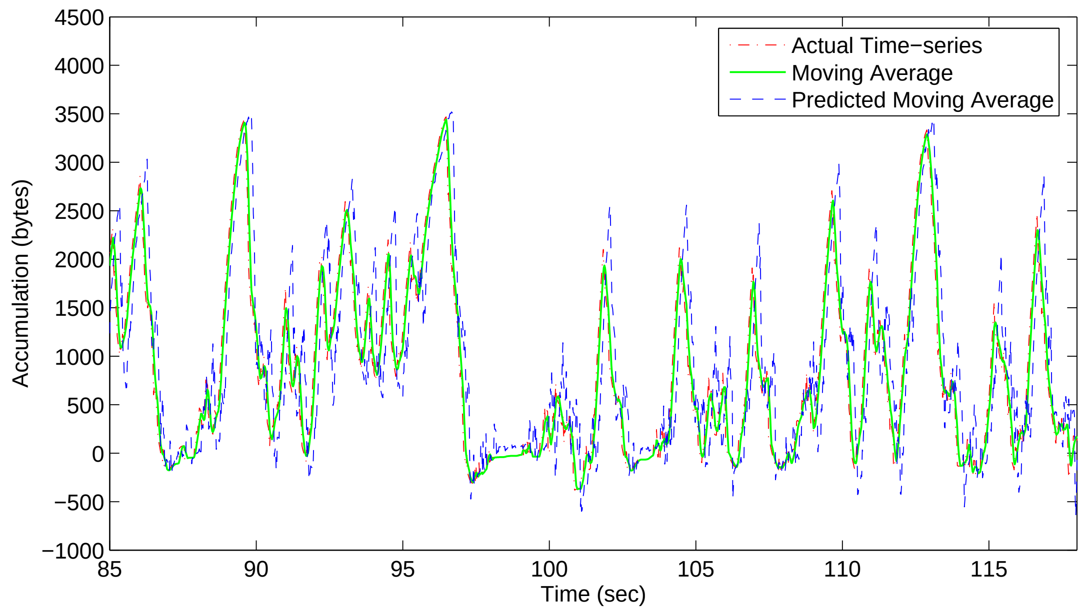


Fig. 15. 240 ms Ahead Prediction of Moving Average Accumulation Using the AR Model; Constant Send Rate of 30 Kbps Having 20 ms Inter-departure Time of the Send Packets.



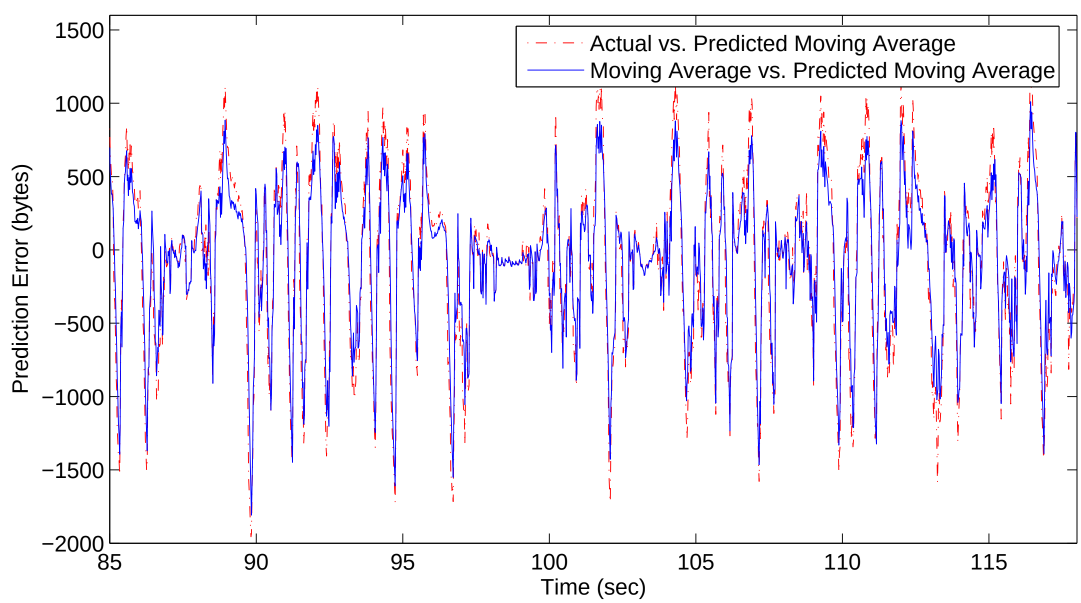
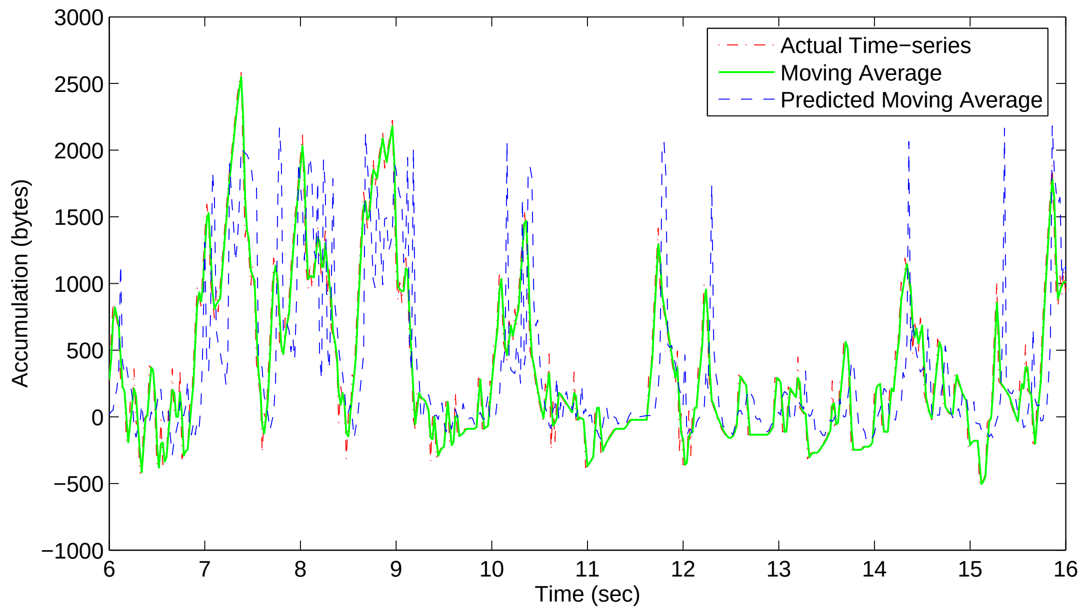


Fig. 16. 240 ms Ahead Prediction of Moving Average Accumulation Using the ARMA Model; Constant Send Rate of 50 Kbps Having 20 ms Inter-departure Time of the Send Packets.



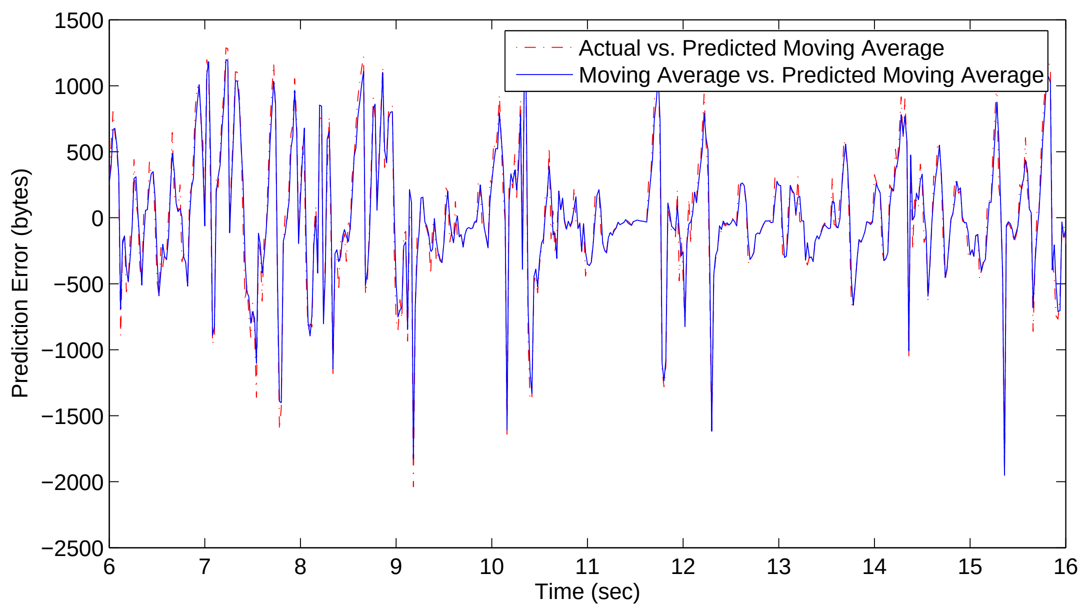


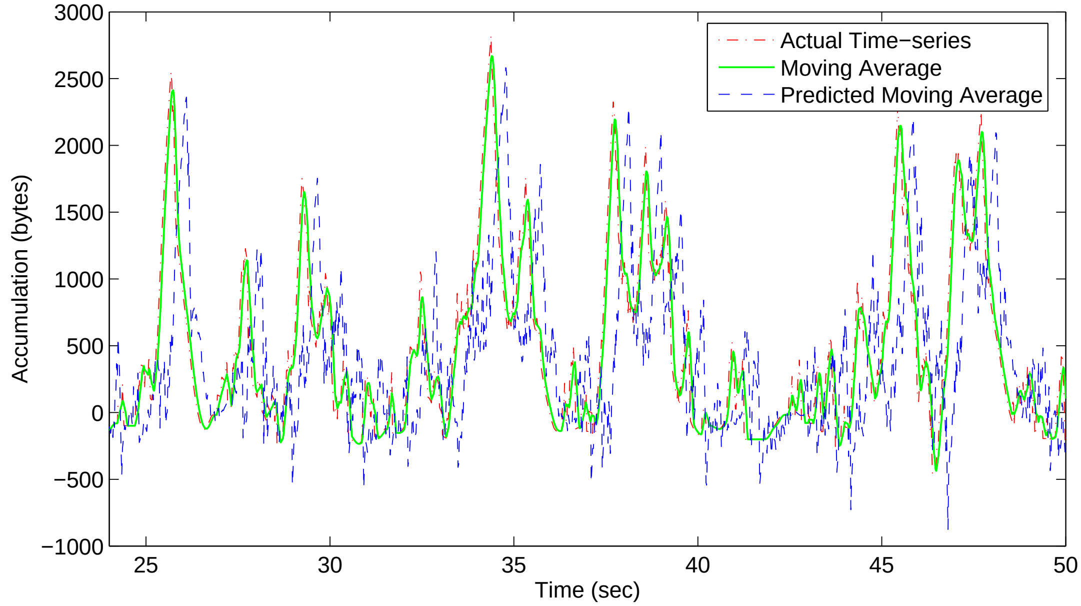
Fig. 17. 240 ms Ahead Prediction of Moving Average Accumulation Using the FMLP Model; Constant Send Rate of 40 Kbps Having 60 ms Inter-departure Time of the Send Packets.

c. 420 ms-Ahead Prediction

For the end-to-end single flows having 60 ms inter-departure time of the send packets, 420 ms ahead means seven step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of send packets, it means twenty-one step-ahead prediction.

Figure 18 shows 420 ms-ahead prediction of moving average accumulation using the AR model. It shows the actual accumulation, the moving average accumulation and the predicted moving average accumulation for a constant send rate of 50 kbps having 20 ms inter-departure time of the send packets. It also shows that AR model fails to perform well for 420 ms-ahead prediction. As can be seen in the figure, prediction error between the predicted moving average accumulation and the actual moving average accumulation is up to 2100 bytes. It also shows very big time-shift between the predicted moving average accumulation and the actual accumulation.

Figure 19 shows the 420-ms ahead prediction of moving average flow accumulation using the ARMA model. It shows 420 ms-ahead prediction for a constant send rate of 40 Kbps having 60 ms packet inter-departure time of the send packets. It shows that ARMA model also does not perform well for 420 ms ahead prediction for end-to-end single flows having 60 ms inter-departure time of the send packets. It should be noted that errors between the predicted moving average accumulation and the actual accumulation is up to 1700 bytes which is equivalent to the height of the spikes in accumulation. From Figures 18 and 19, it can be easily concluded that the predictor performance is extremely bad for the prediction horizon of 420 ms.



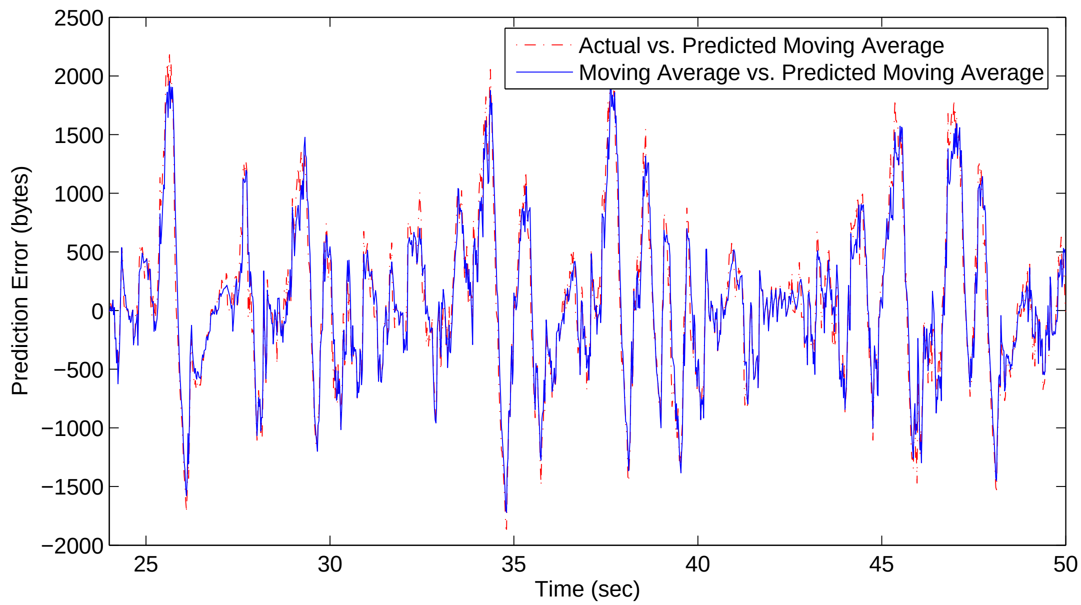


Fig. 18. 420 ms Ahead Prediction of Moving Average Accumulation Using the AR Model; Constant Send Rate of 50 Kbps Having 20 ms Packet Inter-departure Time.

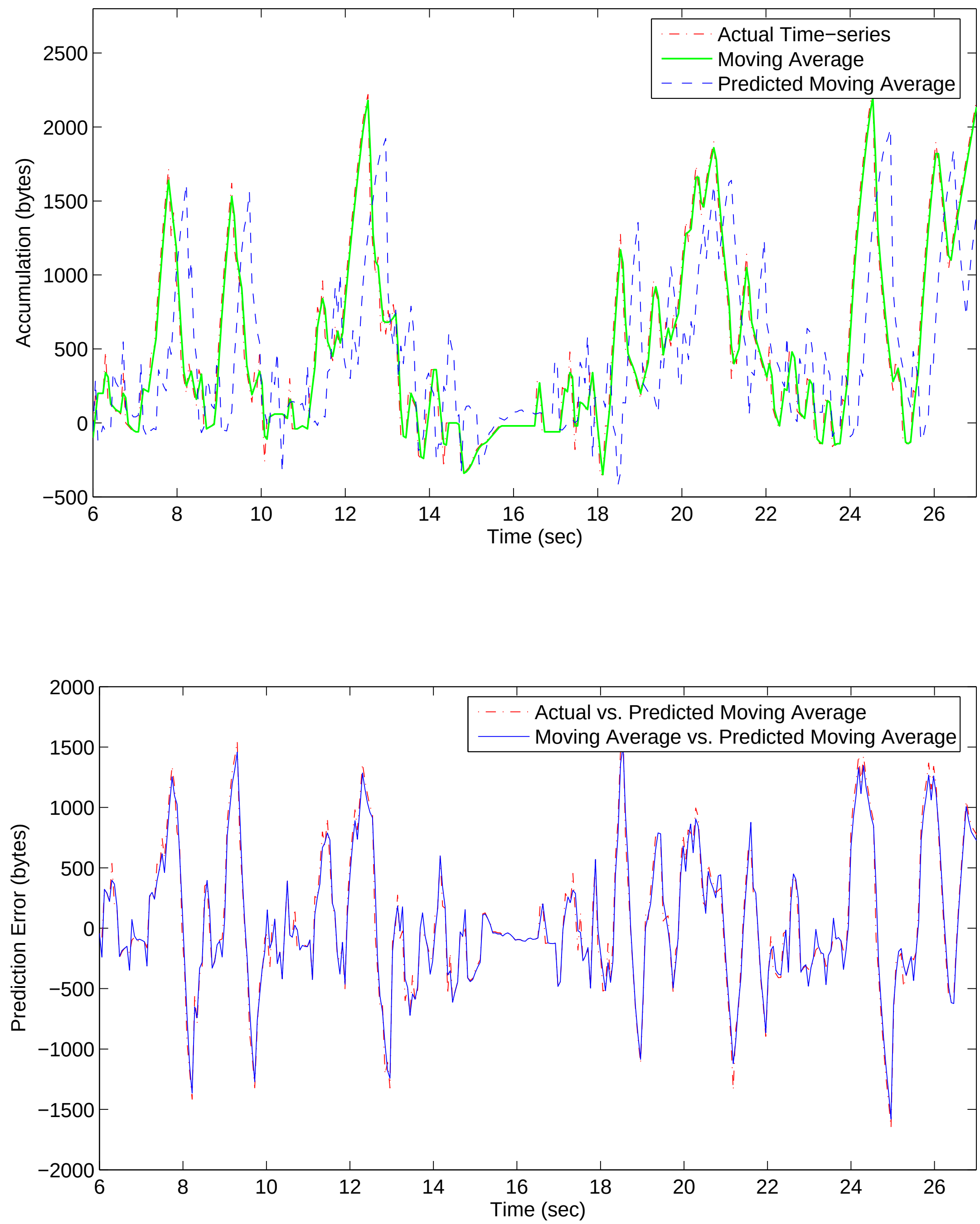


Fig. 19. 420 ms Ahead Prediction of Moving Average Accumulation Using the ARMA Model; Constant Send Rate of 40 Kbps Having 60 ms Packet Inter-departure Time.

2. Comparison of Multi-Step-Ahead Predictor Performance

The results of the MSP on various send-rate cases for AR, ARMA and FMLP predictors are tabulated in this section.

a. 120 ms-Ahead Prediction

Tables III and IV show the performance evaluation results of the AR, ARMA and FMLP models on the various send rate test cases in terms of the performance indicator MSE.

Table III shows 120 ms-ahead prediction results of the AR, ARMA and FMLP model for various send rate cases having 20 ms inter-departure of the send packets. As seen in the table, the MSE results for AR model on different send-rate cases varies between 2.67% to 4.81%, which means that the AR model gives consistent performance for various source send-rate cases. Table also shows that the AR, ARMA and FMLP models perform almost equivalent in all cases.

Table IV shows 120 ms-ahead results for various send rate cases having 60 ms inter-departure time of the send packets. It shows that the performance of AR and ARMA model is similar while the performance of the FMLP model is little worse. Comparison of Tables III and IV indicates that the data-sets having 20 ms packet inter-departure time can be better predicted than the data-sets having 60 ms packet inter-departure time. It can also be concluded that the developed linear and non-linear predictors gives satisfactory 120 ms ahead prediction results for various source send-rates.

Table III. Comparative MSE Results of 120 ms-Ahead Predictions for Send Rate Test Cases Having 20 ms Packet Inter-departure Time.

send rate	AR	ARMA	FMLP
10Kbps	4.81	4.86	5.24
20Kbps	3.69	3.72	3.99
40Kbps	2.67	2.69	2.89
50Kbps	5.65	5.79	5.83
60Kbps	4.14	4.18	4.56

Table IV. Comparative MSE Results of 120 ms-Ahead Predictions for Send Rate Test Cases Having 60 ms Packet Inter-departure Time.

send rate	AR	ARMA	FMLP
10Kbps	7.55	7.91	9.46
20Kbps	10.02	10.13	11.94
40Kbps	8.31	8.36	9.74
50Kbps	10.45	10.70	18.29
60Kbps	8.42	8.41	12.26

b. 240 ms-Ahead Prediction

Tables V and VI show the performance evaluation results of the AR, ARMA and FMLP predictor on the various send rate test cases for 240 ms-ahead prediction.

Table V shows the 240 ms-ahead results for the various send rate cases having 20 ms inter-departure of the send packets. As seen in the table, the performance of the AR model for different send-rate cases varies between 7.76% to 13.01%. It is observed that variation in the prediction performance of the developed models increases as the prediction horizon increases. Table VI shows the 240 ms-ahead results of the AR, ARMA and FMLP predictor for the various send rate cases having 60 ms inter-departure of the send packets. It can been seen from Table VI that AR, ARMA perform almost similar while FMLP results are much worse than the AR and ARMA model. From the tables, it can be concluded that the predictor performance reduces drastically when prediction horizon is increased from 120 ms-ahead prediction to 240 ms-ahead prediction.

Table V. Comparative MSE Results of 240 ms-Ahead Predictions for Send Rate Test Cases Having 20 ms Packet Inter-departure Time.

send rate	AR	ARMA	FMLP
10Kbps	13.10	13.50	18.20
20Kbps	10.30	10.94	12.17
40Kbps	7.76	8.11	11.41
50Kbps	14.99	16.24	19.55
60Kbps	11.05	11.62	15.73

Table VI. Comparative MSE Results of 240 ms-Ahead Predictions for Send Rate Test Cases Having 60 ms Packet Inter-departure Time.

send rate	AR	ARMA	FMLP
10Kbps	16.69	16.54	22.05
20Kbps	21.09	21.65	25.66
40Kbps	18.21	18.86	22.38
50Kbps	21.39	22.56	29.90
60Kbps	17.70	17.91	27.72

c. 420 ms-Ahead Prediction

Table VII shows the 420 ms-ahead results of the AR, ARMA and FMLP predictor for the various send rate cases having 20 ms inter-departure of the send packets. As seen from the table, the performance of the AR model varies from 16.95% to 28.66% for different send-rate cases. It is observed that the variation in the prediction performance is much higher compared to 240 ms-ahead prediction.

Table VII also shows that the AR model performs best for different send-rate cases while FMLP model performs worst for all cases. The FMLP results are as high as 45.63% which indicates bad prediction performance. Table VIII shows the 420 ms-ahead results of the AR, ARMA and FMLP predictor for the various source-send rates having 60 ms inter-departure of the send packets. It can been seen from Table VIII that the AR and ARMA model perform similar while FMLP results are much worse than the AR and ARMA model.

It can be concluded that the predictor performance reduces drastically when prediction horizon in increased 240 ms-ahead prediction to 420 ms-ahead prediction. As seen in tables VII and VIII, developed predictors fail to capture important dynamics of the system and performs bad for all send-rate cases.

Table VII. Comparative MSE Results of 420 ms-Ahead Predictions for Send Rate Test Cases Having 20 ms Packet Inter-departure Time.

send rate	AR	ARMA	FMLP
10Kbps	27.44	29.59	45.63
20Kbps	21.38	23.78	34.17
40Kbps	16.95	18.60	22.68
50Kbps	28.66	32.66	37.04
60Kbps	23.01	25.31	29.38

Table VIII. Comparative MSE Results of 420 ms-Ahead Predictions for Send Rate Test Cases Having 60 ms Packet Inter-departure Time.

send rate	AR	ARMA	FMLP
10Kbps	30.27	29.92	39.58
20Kbps	36.28	37.57	45.53
40Kbps	32.16	33.51	36.26
50Kbps	37.87	40.42	44.88
60Kbps	31.54	32.19	37.45

G. Chapter Overview

This chapter dealt with the training, testing and validation of the linear and nonlinear predictors for the prediction end-to-end single flow characteristics in a simulated network. The various performance metrics used for the evaluation of the predictor are discussed in this chapter. The performance of the linear and non-linear predictors are investigated for different send-rate cases at different time-steps ahead predictions. Also the comparison of various developed predictors for various send rate cases is performed. The effect of various inter-departure time of the send packets on prediction performance is also analyzed in this chapter. It is observed that the predictors perform well for single-step ahead prediction but their performance reduces drastically when the prediction horizon is increased beyond 240 ms.

CHAPTER V

END-TO-END SINGLE FLOW PREDICTION FOR ACTUAL TRAFFIC DATA

A. Introduction

After obtaining good prediction results for simulated traffic data, next step is to investigate the performance of the empirical models for measured traffic data. This chapter is mainly divided in two sections: path-dependent predictors and path-independent predictors. In path-dependent predictors section, predictors are developed for a particular pair of source and destination nodes and their performance is then evaluated on the same pair for which it was developed. While in path-independent predictors section, predictors are developed for a particular pair of source and destination nodes and their performance is then evaluated for different pair of source and destination nodes. Data used in this chapter is collected from a PlanetLab network.

B. Performance Metrics

In this research, Mean Square Error(MSE) is used as a performance metric for the predictors developed. It is defined as the ratio between the sum of the square of the prediction error and the sum of the square of the input data. MSE can be represented by the following equation:

$$MSE = \frac{\sum_{k=1}^{N} \left(x(k) - \widehat{x}(k|k-1)\right)^2}{\sum_{k=1}^{N} x(k)^2} \times 100 \tag{5.1}$$

where N is the total number of data points, $x(k)$ is the actual value of the output, and $\widehat{x}(k|k-1)$ is the prediction value of the output. MSE can be also defined as the inverse of *Signal-To-Noise Ratio*(SNR). MSE considered as one of the best performance metric that gives a good picture on the quality of the predictor.

C. Path-dependent Predictors

Path-dependent predictors means that the predictor is developed for a particular pair of source and destination nodes and their performance is then evaluated for data-sets collected from the same pair of source and destination nodes. Results of two different pairs of source and destination nodes is presented in this section.

1. Description of Training and Validation Data Sets

As discussed earlier, data-sets used in this section is measured from the PlanetLab network. As present research is more interested in a congested network, data-sets having than 3% losses are only used for modeling and testing of models. That means it is assumed that the network is congested if the total loss in the collected data-sets is more than 3%.

Two different sets of source and destination pair are selected and various linear and non-linear predictors are individually developed for each source and destination pair. Table IX shows two pair of source and destination nodes used in present section. Henceforth, Ucsd3-Niml node pair will be referred as node pair 1 and Niml-seattle3 pair will be referred as node pair 2. Details of the data-collection process have been explained in Chapter III.

Table IX. Source and Destination Nodes on PlanetLab Used for Data Collection.

Soure Node	Destination Node	Name
Ucsd3(PlanetLab)	Niml (TAMU)	Node pair 1
Niml (TAMU)	Seattle3 (PlanetLab)	Node pair 2

Two different sets of linear and non-linear predictors are developed and tested for 20 ms and 60 ms inter-departure time of the send packets. Two sets of AR,ARMA and FMLP models, for 20 ms and 60 ms inter-departure time of the send packets have been developed for both source-destination pairs. Hence, in total four sets of AR, ARMA and FMLP predictors are developed and validated in present section. In all cases, the linear and non-linear predictors are developed at a source-rate of 30 Kbps. Performance of the developed models is then evaluated by varying the source send-rate between 20 Kbps to 50 Kbps. Here, source send-rate is varied by changing the packet-size of send packets. It is important to note that the inter-departure time and the packet-size of the sent flow are constant for a particular session. For every source-send rate, performance of the developed predictors are validated for 5 data-sets collected during different time of the day. This has been done to gauge the predictor performance under varying cross-traffic conditions.

The network accumulation for each traces is calculated by periodically calculating cumulative send and arrival flow at the source and the destination. The time interval used for measuring cumulative flows is equal to the inter-departure time of send packets. The data-sets is then processed before using for modeling and testing of the predictive models.

Processing of the data-sets includes two steps. In the first step, the trend is removed from the total accumulation to calculate present accumulation in the network. In the second step, the time-series of the moving average of present accumulation is calculated for system identification purpose. Here, the trend is dynamically calculated by adding mean slope of last 1 second window to the current value of the trend. The moving average window is set as 120 ms and the window is moved by one sample i.e. window is moved by 20 ms if the sampling time is 20 ms and 60 ms if the sampling time is 60 ms.

2. Development of Linear and Non-linear Predictors

The next step is to use system identification techniques to obtain the best empirical model. For each source and destination pair, two different sets of linear and non-linear predictors are developed for 20 ms and 60 ms packet inter-departure time of the send packets. In all cases, the linear and non-linear predictors are developed at 30 Kbps source send-rate.

For Node pair 1, after various permutations and combinations, an AR predictor with model structure {35} and ARMA with model structure {32 8} give the best fit for the training data-set having 20 ms inter-departure time of the send packets. This means that 35 past outputs have been used in the AR model and 32 past outputs and 8 past noise terms have been used in the ARMA model. The model order is very high in this case which indicates the long term dependency of the data-sets. For the data-sets having 60 ms inter-departure time of the send packets, an AR predictor with model structure {17} and ARMA with model structure {17 3} have been found to be most suitable for the prediction. There are no inputs for the predictors as the cross-traffic, which has the highest impact on the flow characteristics, cannot be measured and it is considered as a disturbance of the model.

Training method of non-linear predictor is completely different from the linear models. Selecting model-structure and parameters of non-linear model is very time consuming and effort taking process. After extensive search over several possible FMLP architectures, FMLP model structure {26 3 1} which translates into 26 input layer nodes, 3 hidden layer nodes and 1 output layer is found to be the best model-structure for the training data-sets having 20 ms inter-departure time of the send packets. Similarly for the training data-set having 60 ms packet inter-departure time , most suitable FMLP model structure is {11 3 1}.

Similar process is performed for the data-sets of Node pair 2. An AR predictor with model structure {29} and ARMA with model structure {24 7} give the best fit for the training data-set having 20 ms inter-departure time of the send packets. For the data-sets having 60 ms inter-departure time of the send packets, an AR predictor with model structure {12} and ARMA with model structure {16 5} have been found to be most suitable for the prediction.

After extensive search over several possible FMLP architectures, FMLP model structure {21 4 1} is found to be the best model-structure for the training data-sets having 20 ms inter-departure time of the send packets. Similarly for the training data-set having 60 ms packet inter-departure time , most suitable FMLP model structure is {11 3 1}.

During the training process the performance of the predictor is determined using the mean square error of the signal. It is important to observe that the order of the model structure reduces when the inter-departure time of send packet is increased.

3. Single-Step Ahead Prediction

A single step-ahead prediction is a first step in evaluating the performance of any developed predictor. SSP in following cases means 20 ms ahead prediction for the data-sets having 20 ms inter-departure time of the send packets and 60 ms ahead prediction for the data-sets having 60 ms inter-departure time of the send packets.

a. Performance Evaluation of Single-Step-Ahead Predictors

Performance evaluation of the trained linear and non-linear predictors is presented in this section. This is done by testing each of these models for different source send-rate test cases.

For the sake of clarity of the presented results, all figures show only 500-1000

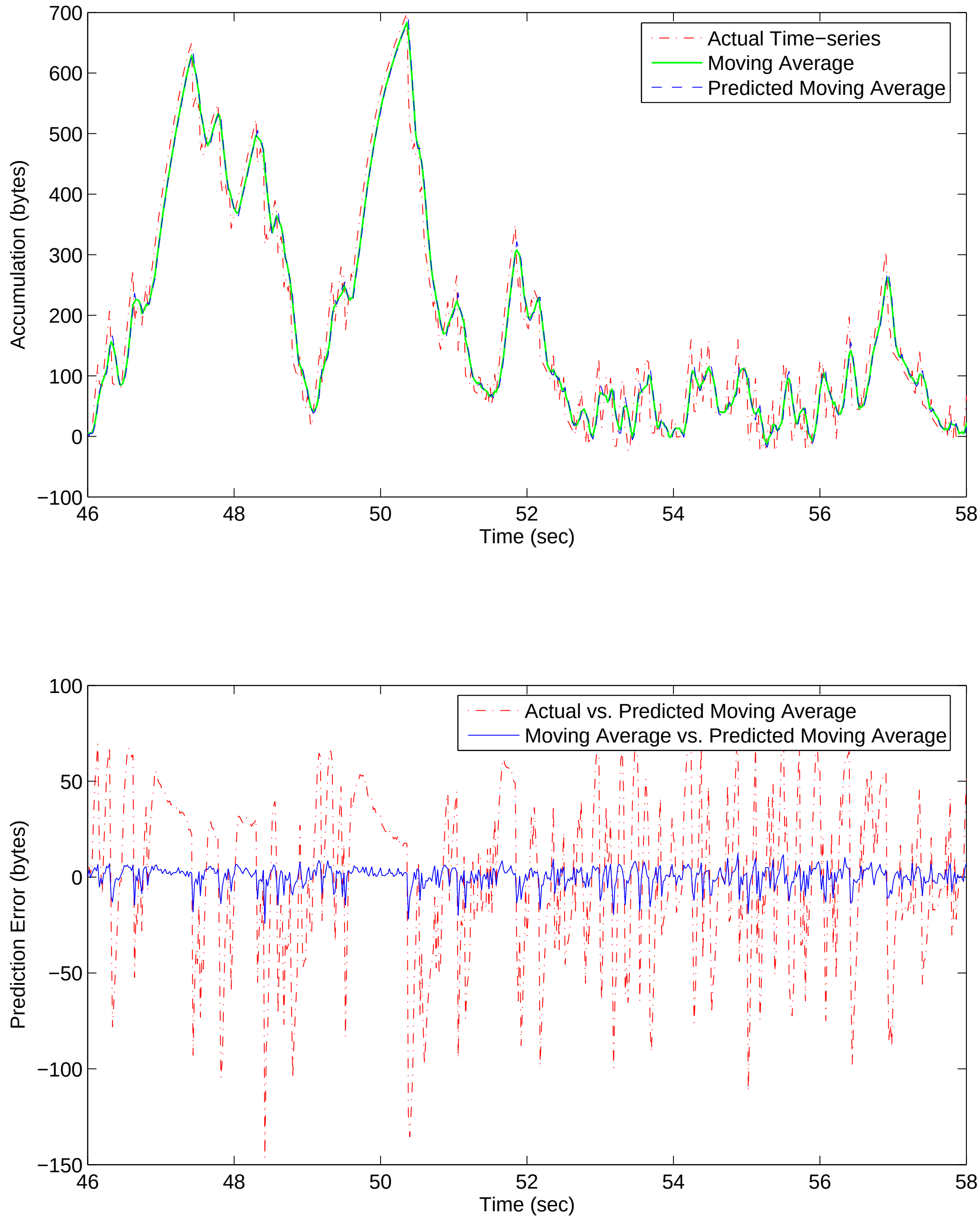


Fig. 20. Single-Step-Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the AR Model ; Constant Send Rate of 20 Kbps with 20 ms Packet Inter-departure Time.

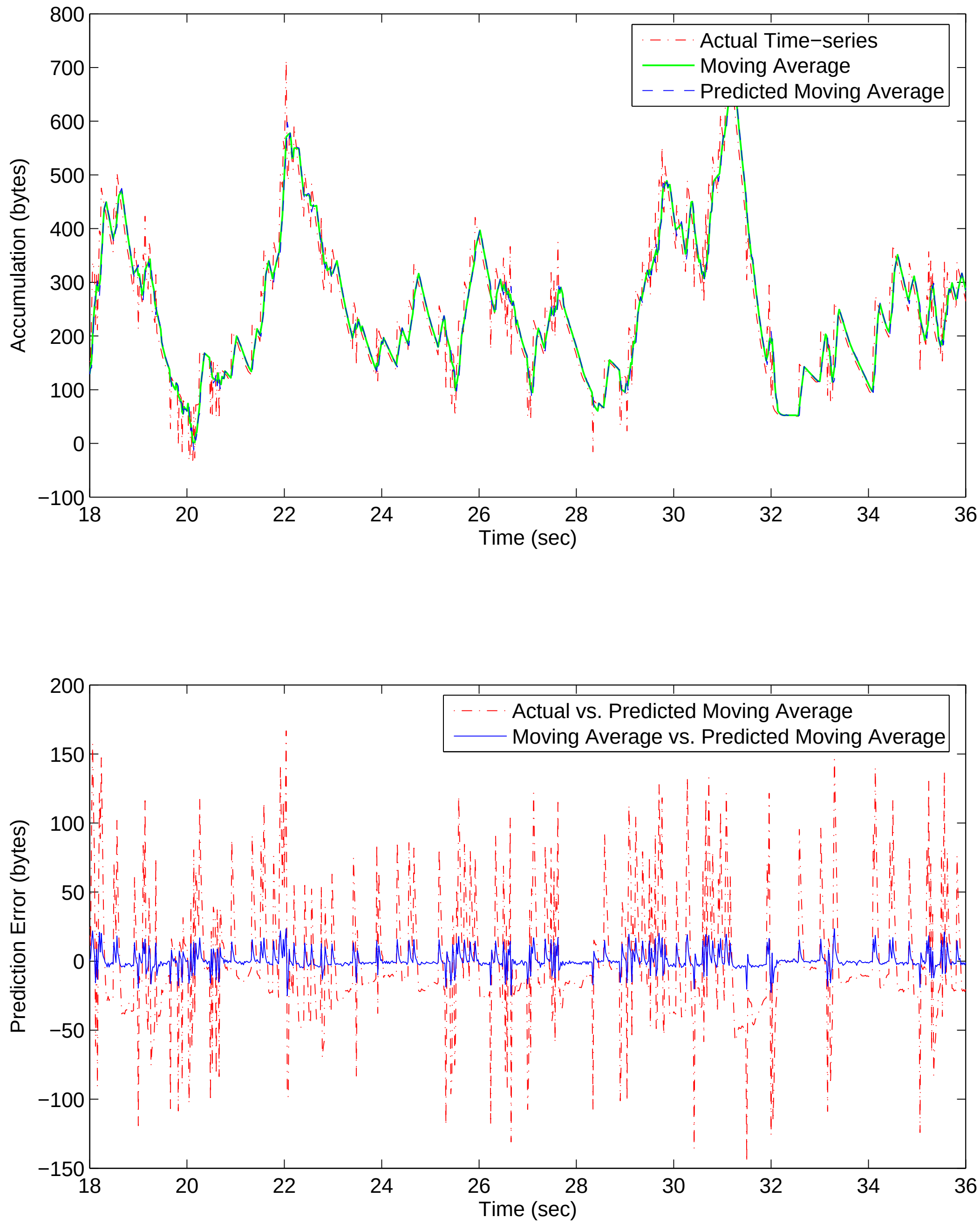


Fig. 21. Single-Step-Ahead Prediction of Moving Average Accumulation on Node Pair 2 Using the ARMA Model ; Constant Send Rate of 30 Kbps with 20 ms Packet Inter-departure Time.

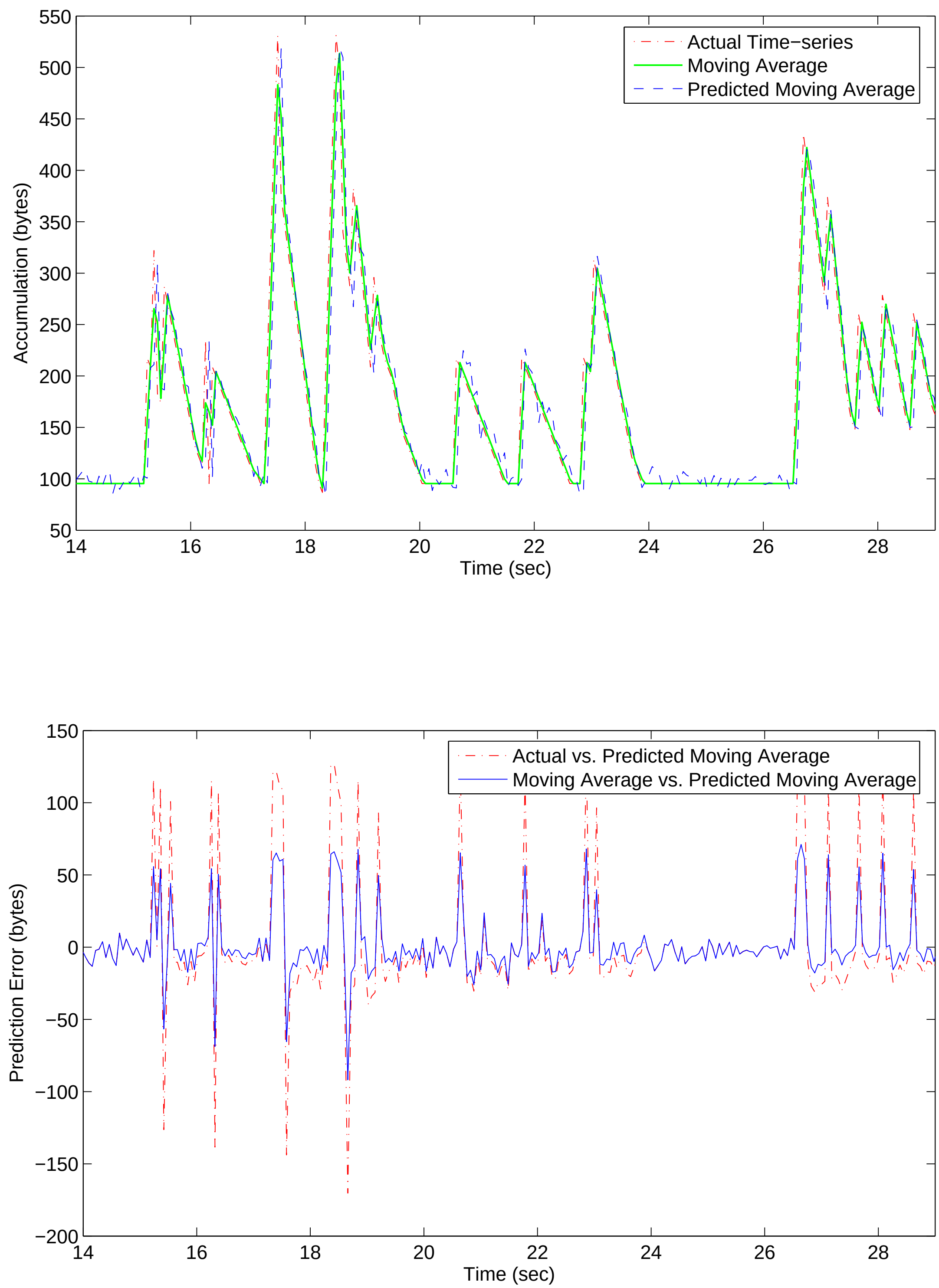


Fig. 22. Single-Step-Ahead Prediction of Moving Average Accumulation on Node Pair 2 Using the AR Model ; Constant Send Rate of 10 Kbps with 60 ms Packet Inter-departure Time.

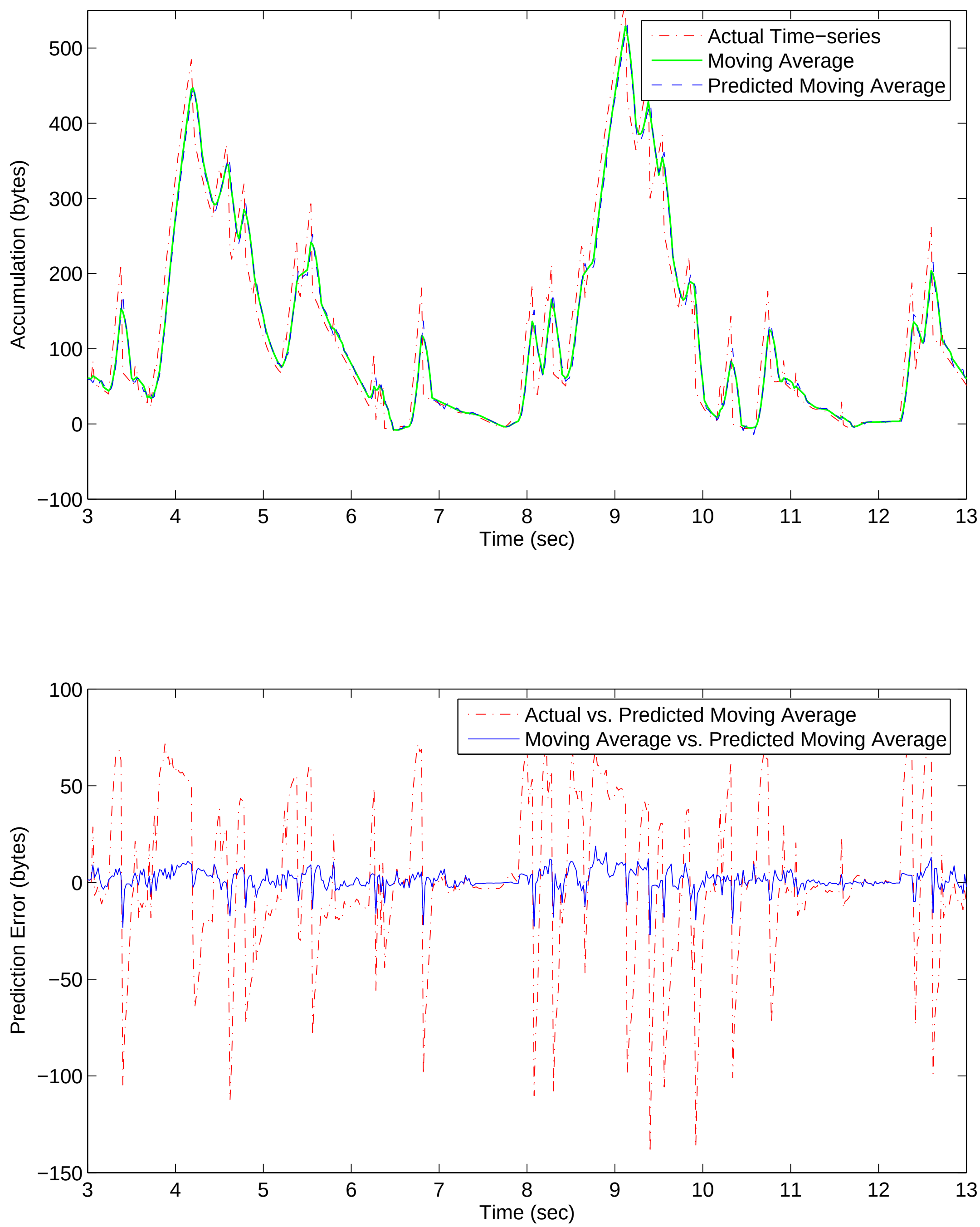


Fig. 23. Single-Step-Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the FMLP Model ; Constant Send Rate of 40 Kbps with 20 ms Packet Inter-departure Time.

samples of the data-sets.

Figure 20 shows the SSP of moving average accumulation using the AR model. It depicts the actual accumulation, the moving average accumulation and the predicted moving average accumulation on node pair 1 for a constant send rate of 20 Kbps with 20 ms inter-departure time of the send packets. It shows that the AR model can capture the dynamics of the network for SSP. It should be noted that the maximum prediction error between the predicted moving average accumulation and actual accumulation is less than 150 bytes.

Figure 21 shows the SSP of moving average accumulation using the ARMA model. It shows the prediction of moving average accumulation on node pair 2 for a constant send rate of 30 Kbps with 20 ms inter-departure time of send packets. It depicts that the SSP of ARMA model is also accurate.

Figure 22 shows the SSP of moving average accumulation for Node pair 2 using the AR model. It shows the prediction of moving average accumulation for a constant send rate of 10 Kbps with 60 ms inter-departure time of the send packets. The figure shows that the SSP of accumulation for node pair 2 is also accurate.

Figure 23 shows the SSP of moving average accumulation using the FMLP model. It shows the actual accumulation, the moving average accumulation and the predicted moving average accumulation on Node Pair 1 for a constant send rate of 40 Kbps with 20 ms inter-departure time of the send packets.

Above figures indicates that AR, ARMA and FMLP models perform similar for the SSP of moving average accumulation. They also indicate that the developed models are accurate in the single step-ahead prediction of actual accumulation.

b. Comparison of Single-Step-Ahead Predictor Performance

The results of the SSP using AR, ARMA and FMLP predictors are tabulated in this section. Following tables show the performance evaluation results in terms of the performance indicator MSE. As discussed earlier, 5 data-sets are collected for every source send-rate and tables show mean, minimum and maximum value of MSE for all send-rate cases.

Tables X and XI show the performance evaluation results of the AR, ARMA and FMLP predictors for the various send rate test cases on node pair 1. Similarly, Tables XII and XIII show the performance evaluation results of the AR, ARMA and FMLP predictors for the various send rate test cases on node pair 2. Table X shows that AR, ARMA and FMLP results perform similar for various send rate cases with 20 ms inter-departure time of the send packets. It also shows that maximum MSE for the developed predictors are not very high, which suggests that the performance of developed predictors is consistent under varying cross-traffic conditions. Table XI shows the SSP results of the AR, ARMA and FMLP predictors for various send rate cases having 60 ms inter-departure of the send packets. Table XI also shows that the AR, ARMA and FMLP models perform similarly for SSP. Table XII shows that the SSP results of the AR, ARMA and FMLP predictors on node pair 2 for various send rate cases with 20 ms inter-departure of the send packets.

Table XII shows that AR, ARMA and FMLP models performs accurately for various send rate cases having 20 ms inter-departure time of send packet. Table XIII shows that the SSP results of the AR, ARMA and FMLP predictor for the various send rate cases having 60 ms inter-departure of the send packets. From the following tables, it can be concluded that the developed linear and non-linear predictors give accurate single-step ahead prediction results for both node pairs 1 and 2.

Table X. Comparative MSE Results of Single-Step-Ahead Predictions for Node Pair 1; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	1.05	0.57	2.39	1.04	0.56	2.36	1.08	0.57	2.40
30Kbps	1.66	1.30	3.91	1.64	1.28	3.88	1.63	1.35	3.96
40Kbps	1.48	1.22	2.68	1.44	1.20	2.66	1.57	1.27	3.69
50Kbps	1.47	0.90	2.91	1.45	0.85	2.98	1.54	0.98	3.09

Table XI. Comparative MSE Results of Single-Step-Ahead Predictions for Node Pair 1; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	2.48	1.01	3.37	1.81	0.94	5.26	2.04	1.07	5.56
30Kbps	1.99	0.96	3.17	2.54	1.31	3.54	2.64	1.22	3.51
40Kbps	2.77	1.37	3.65	2.46	0.84	3.61	2.84	1.17	3.91
50Kbps	2.65	0.84	3.71	3.13	1.26	4.40	3.17	1.69	4.67

Table XII. Comparative MSE Results of Single-Step-Ahead Predictions for Node Pair 2; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	1.59	0.40	3.20	1.56	0.39	3.90	1.60	0.44	3.10
30Kbps	1.72	0.24	5.07	1.69	0.22	5.82	1.70	0.26	5.64
40Kbps	1.66	0.23	7.07	1.62	0.26	8.82	1.67	0.28	7.63
50Kbps	1.48	0.49	6.92	1.65	0.48	6.59	1.75	0.53	6.84

Table XIII. Comparative MSE Results of Single-Step-Ahead Predictions for Node Pair 2; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	3.46	0.70	5.90	3.54	0.81	6.14	4.51	1.57	6.16
30Kbps	4.48	0.75	7.29	5.15	0.80	6.92	5.56	0.73	7.31
40Kbps	4.30	0.19	7.12	4.28	0.32	6.48	5.32	0.27	7.33
50Kbps	3.92	1.08	6.03	3.78	1.83	7.21	4.80	1.32	6.87

4. Multi-Step Ahead Prediction

The present section explores the multi-step-ahead prediction of the developed linear and non-linear predictors.

a. Performance Evaluation of Multi-Step-Ahead Predictors

The send-rate test cases used for evaluating the MSP predictors are same as the send-rate cases used for evaluating SSP predictors. This will be helpful in comparing various time-step-ahead predictors on a common scale.

Multi-step ahead prediction contains three sections: 120 ms-ahead prediction, 240-ms ahead prediction and 420 ms-ahead prediction. The motivation for selecting certain time ahead prediction instead of number of step ahead prediction is to examine the effect of packet inter-departure time on the prediction performance. With certain time ahead prediction, it becomes easier to compare prediction results for data-sets having 20 ms and 60 ms inter-departure time of send packets.

120 ms-Ahead Prediction:

For the end-to-end single flows having 60 ms inter-departure time of the send packets, 120 ms ahead prediction means two step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of the send packets, it means six step-ahead prediction.

Figure 24 shows the 120 ms-ahead prediction of moving average accumulation using the AR model. It depicts the actual accumulation, the moving average accumulation and the predicted moving average accumulation on node pair 1 for a constant send rate of 20 Kbps with 20 ms inter-departure time of the send packets. It shows that the AR model can perform well for the 120 ms-ahead prediction of moving average accumulation. It should be noted that the maximum prediction error between the predicted moving average accumulation and actual accumulation is less than 350 bytes.

Similarly, Figure 25 shows the 120 ms-ahead prediction of moving average accumulation using the FMLP model. It shows the prediction of moving average accumulation on node pair 2 for a constant send rate of 10 Kbps with 20 ms inter-departure time of send packets. It shows that the FMLP model also performs well for the 120 ms-ahead prediction of moving average accumulation. Figure 26 shows the 120 ms-ahead prediction of moving average accumulation using the ARMA model. It shows the prediction of moving average accumulation on node pair 1 for a constant send rate of 30 Kbps with 60 ms inter-departure time of the send packets.

Figure 27 shows the 120 ms-ahead prediction of moving average accumulation using the AR model. It shows the actual accumulation, the moving average accumulation and the predicted moving average accumulation on node pair 1 for a constant send rate of 10 Kbps with 60 ms inter-departure time of the send packets. Above figures indicate that the developed models are reasonably accurate for the 120 ms-ahead prediction of the actual accumulation.

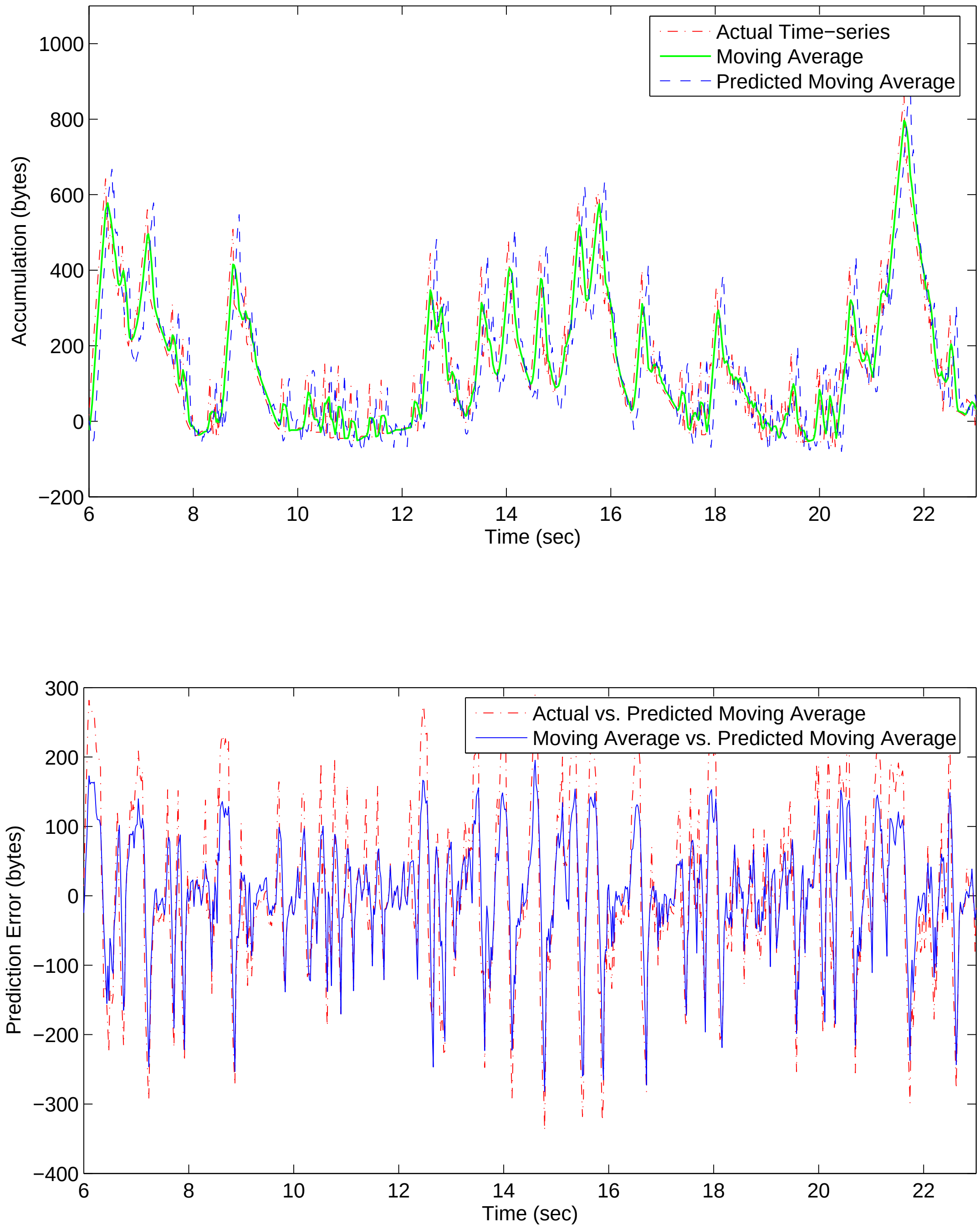


Fig. 24. 120 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the AR Model; Constant Send Rate of 20 Kbps with 20 ms Packet Inter-departure Time.

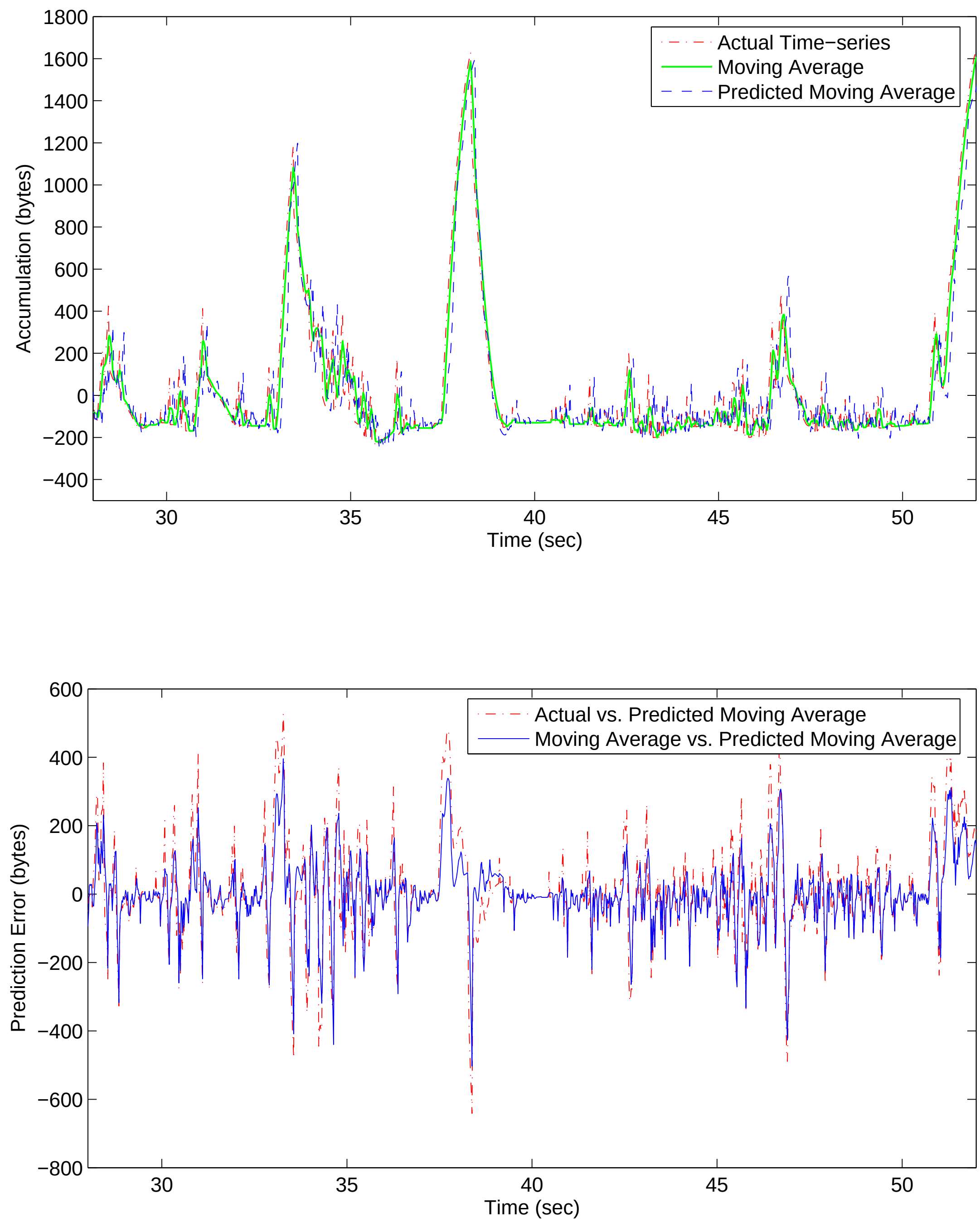
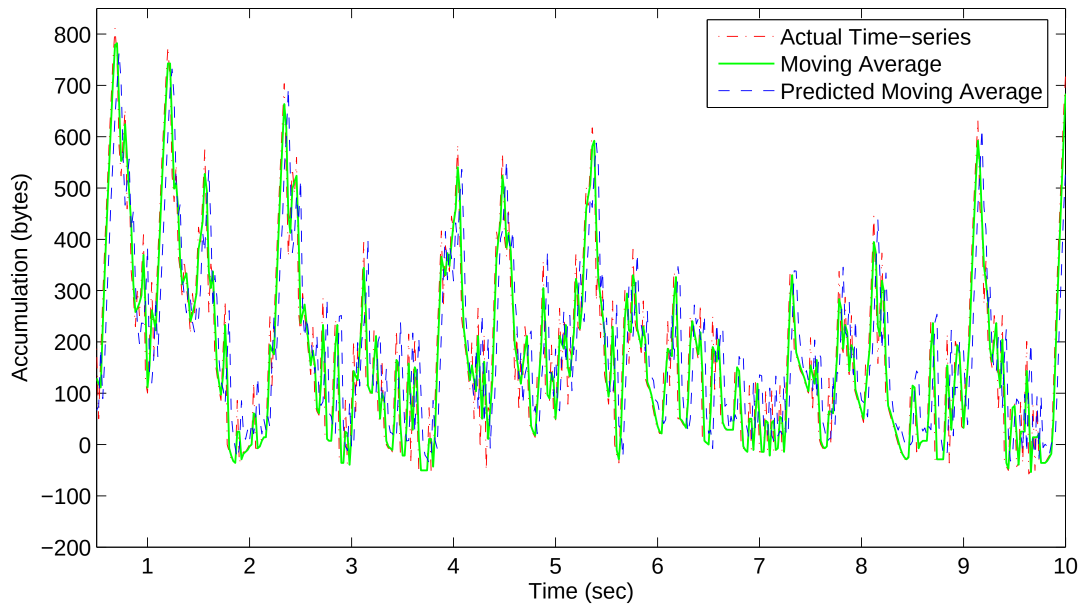


Fig. 25. 120 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the FMLP Model; Constant Send Rate of 10 Kbps with 20 ms Packet Inter-departure Time.



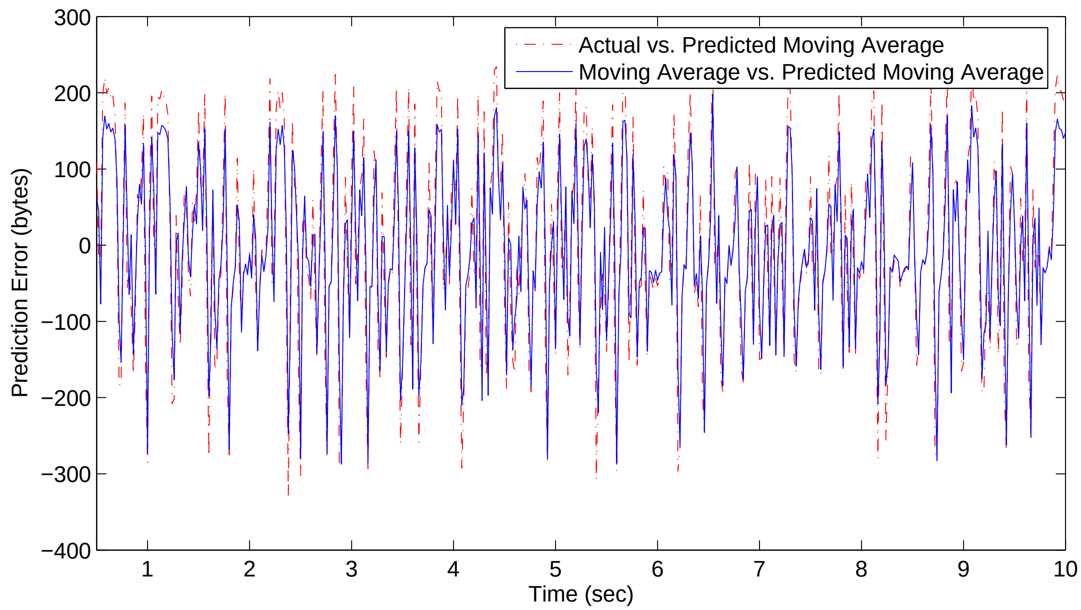
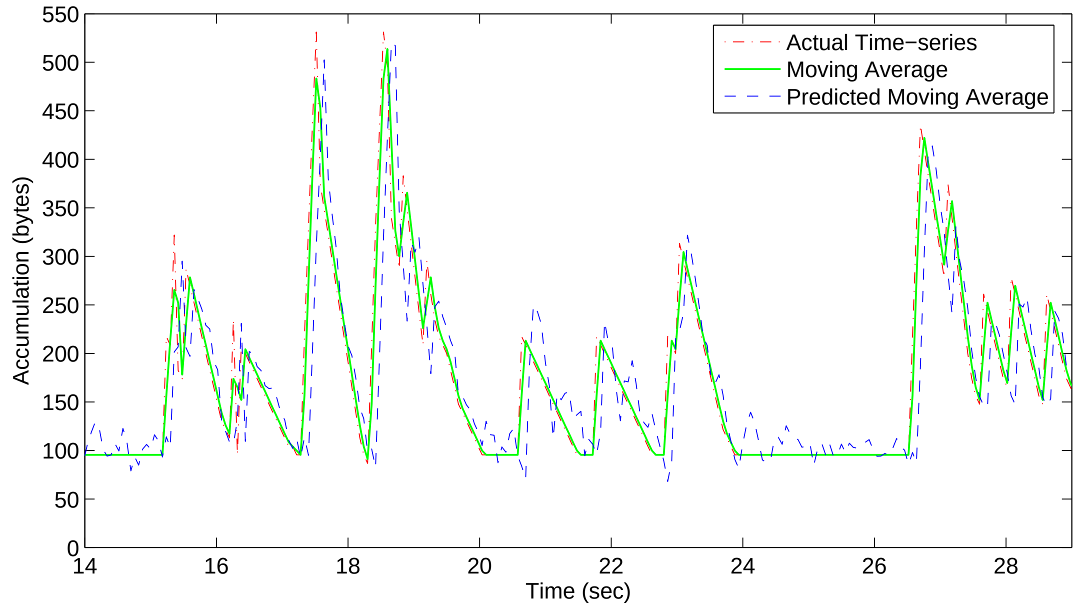


Fig. 26. 120 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the ARMA Model; Constant Send Rate of 30 Kbps with 60 ms Packet Inter-departure Time.



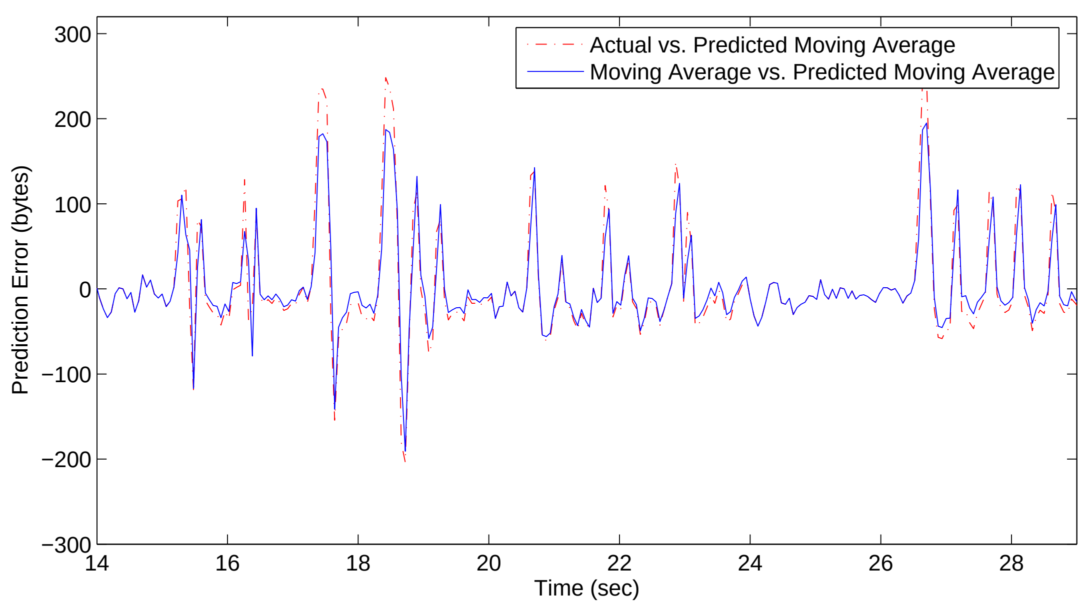


Fig. 27. 120 ms Ahead Prediction of Moving Average Accumulation on Node Pair 2 Using the AR Model; Constant Send Rate of 10 Kbps with 60 ms Packet Inter-departure Time.

240 ms-Ahead Prediction:

For the end-to-end single flows having 60 ms inter-departure time of the send packets, 240 ms ahead prediction means four step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of the send packets, it means twelve step-ahead prediction.

Figure 28 shows the 240 ms-ahead prediction of moving average accumulation using the FMLP model. It depicts the actual accumulation, the moving average accumulation and the predicted moving average accumulation on node pair 1 for a constant send rate of 50 Kbps with 60 ms inter-departure time of the send packets. Although the prediction errors are high in this case, the developed model can capture some important dynamics of the network. Figure 29 shows the 240 ms-ahead prediction of moving average accumulation using the AR model. It shows the prediction of moving average accumulation on node pair 2 for a constant send rate of 10 Kbps with 60 ms inter-departure time of send packets. It should be noted that maximum prediction error in this case is as less as 230 bytes. But at the same time, the maximum height of the moving average accumulation is less than 550 bytes.

Figure 30 shows the 240 ms-ahead prediction of moving average accumulation using the ARMA model. It shows the prediction of moving average accumulation on node pair 1 for a constant send rate of 50 Kbps with 20 ms inter-departure time of the send packets. Figure 31 shows the 240 ms-ahead prediction of moving average accumulation using the AR model. It shows the actual accumulation, the moving average accumulation and the predicted moving average accumulation on node pair 1 for a constant send rate of 40 Kbps with 20 ms inter-departure time of the send packets. Above figures indicate that the prediction performance of the developed models are acceptable.

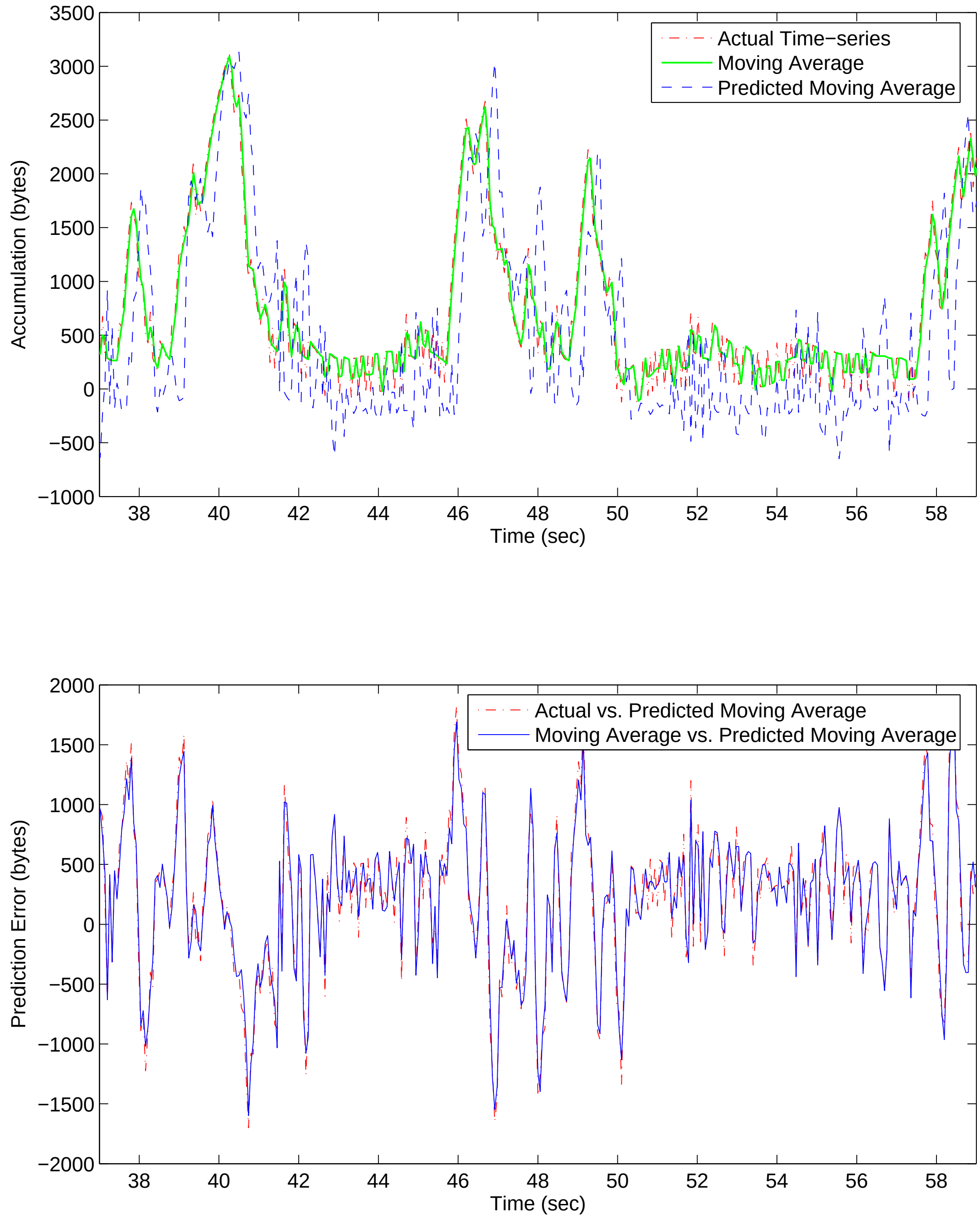


Fig. 28. 240 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the FMLP Model; Constant Send Rate of 50 Kbps with 60 ms Packet Inter-departure Time.

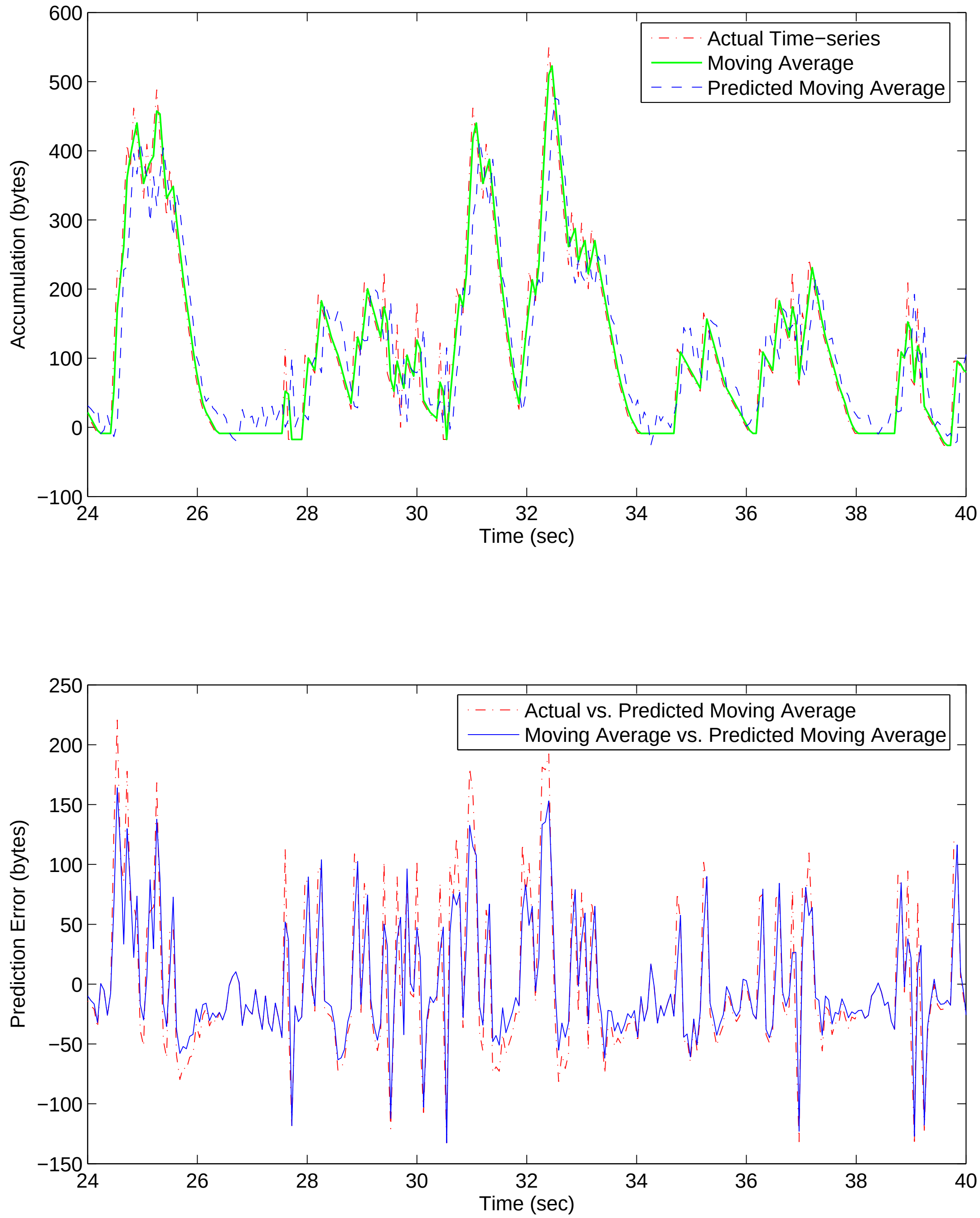
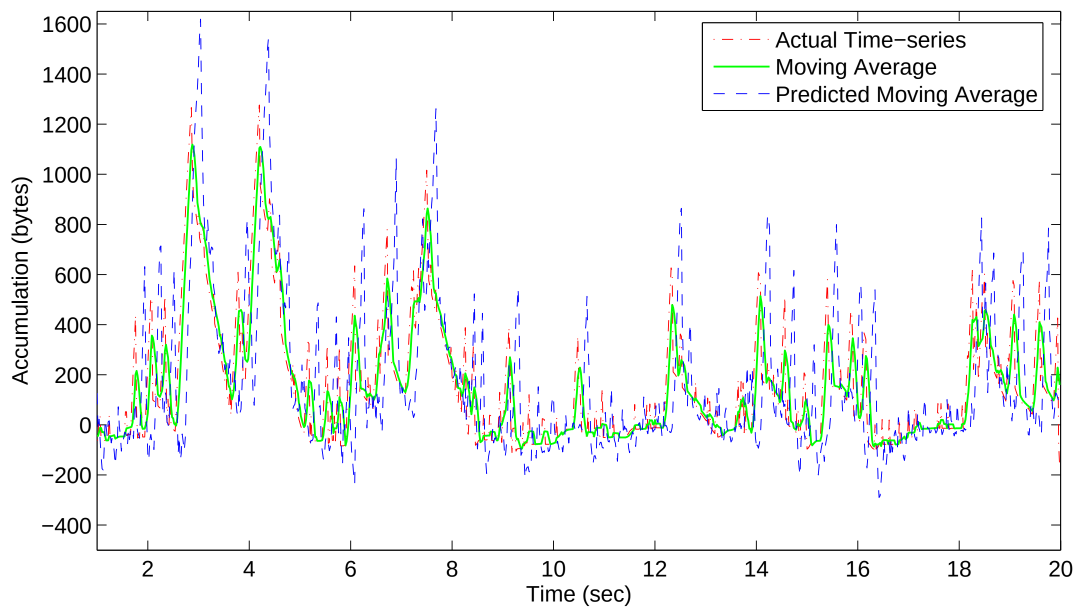


Fig. 29. 240 ms Ahead Prediction of Moving Average Accumulation on Node Pair 2 Using the AR Model; Constant Send Rate of 10 Kbps with 60 ms Packet Inter-departure Time.



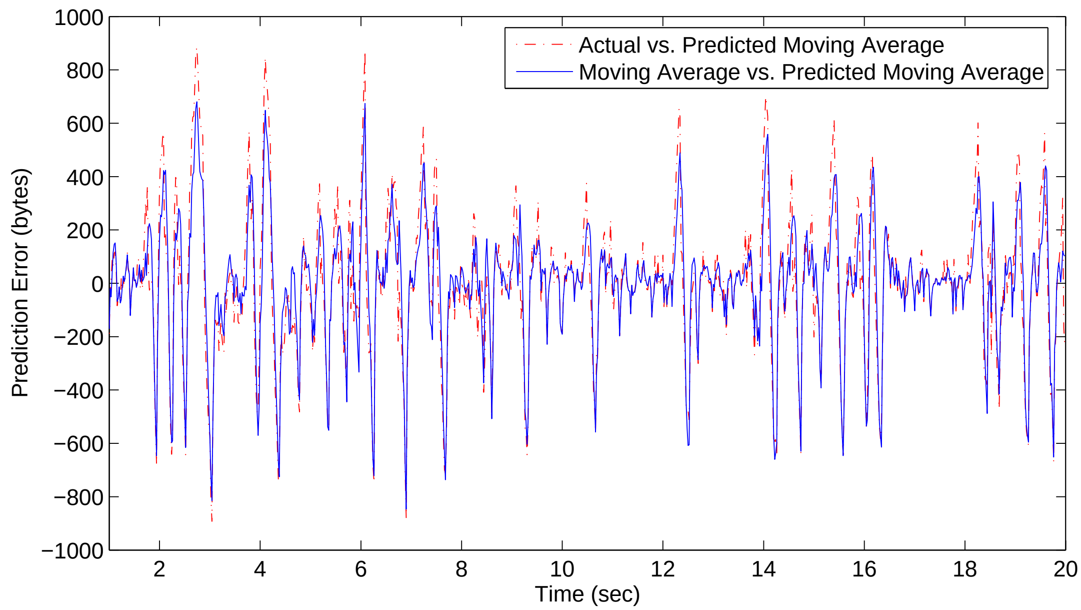
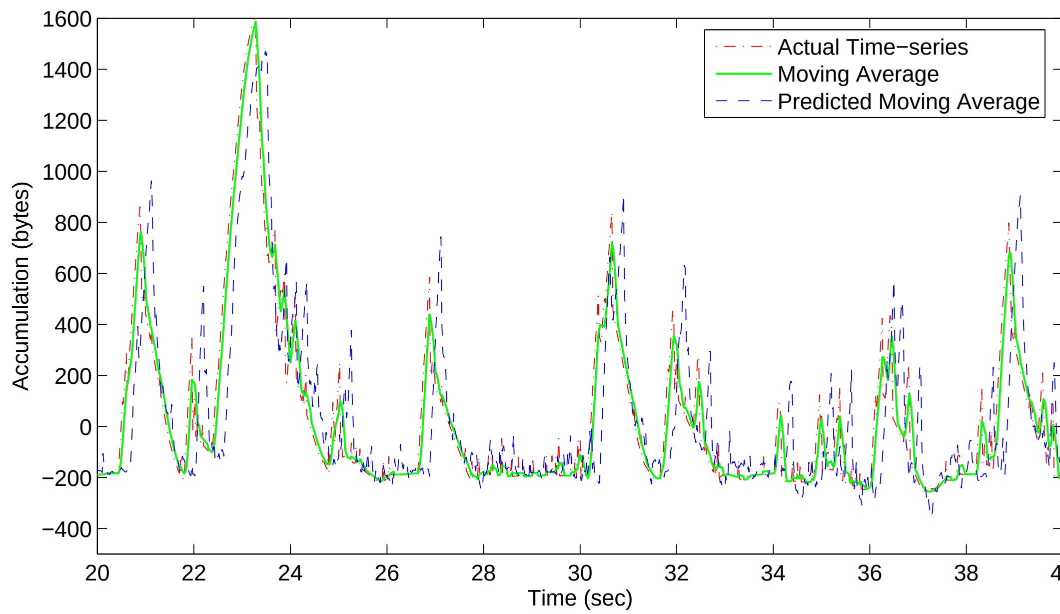


Fig. 30. 240 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the ARMA Model; Constant Send Rate of 50 Kbps with 20 ms Packet Inter-departure Time.



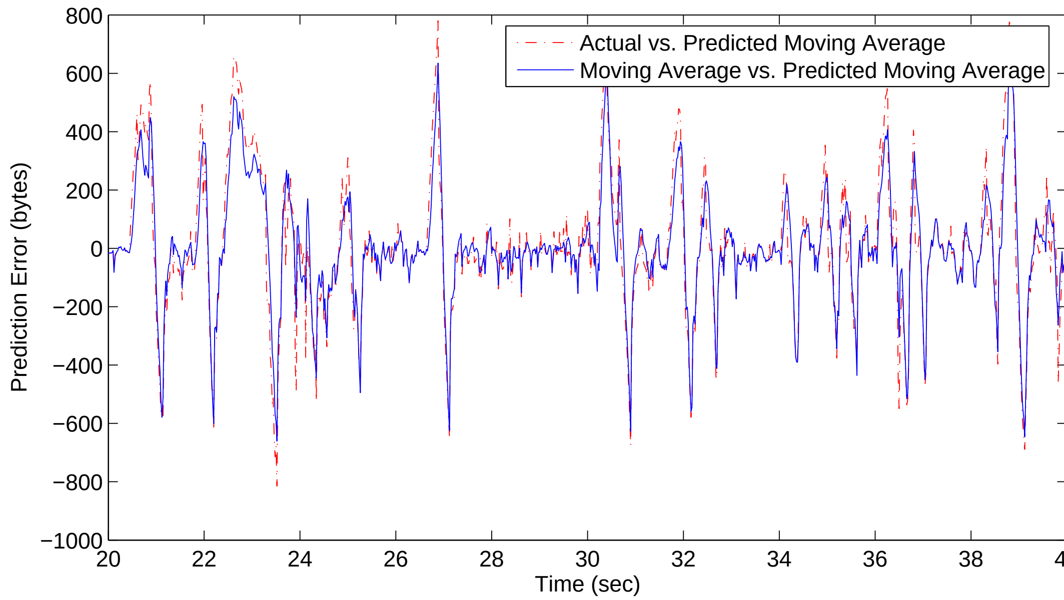


Fig. 31. 240 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the AR Model; Constant Send Rate of 40 Kbps with 20 ms Packet Inter-departure Time.

Some time-shift between the predicted moving average accumulation and the actual accumulation is also observed in all cases.

420 ms-Ahead Prediction:

For the end-to-end single flows having 60 ms inter-departure time of the send packets, 420 ms ahead prediction means seven step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of the send packets, it means twenty-one step-ahead prediction. Figure 32 shows the 420 ms-ahead prediction of moving average accumulation using the AR model. It depicts the actual accumulation, the moving average accumulation and the predicted moving average accumulation node pair 1 for a constant send rate of 30 Kbps on with 20 ms inter-departure time of the send packets. It shows that the developed AR model fails to perform well for 420 ms-ahead prediction. Figure 33 shows the 420 ms-ahead prediction of moving average accumulation using the FMLP model. It shows the prediction of moving average accumulation on node pair 1 for a constant send rate of 10 Kbps with 20 ms inter-departure time of send packets. It can be observed from the figure that the FMLP model completely misses spikes and is unable to capture the dynamics of the network. Figure 34 shows the 420 ms-ahead prediction of moving average accumulation using the ARMA model. It shows the prediction of moving average accumulation on node pair 1 for a constant send rate of 30 Kbps with 60 ms inter-departure time of the send packets. From the figures, it can be easily concluded that predictor performance is extremely bad for 420ms prediction horizon. It can also be observe that the predictors especially perform bad for sudden increase and decrease of the accumulation. Time-shift between the predicted moving average accumulation and the actual accumulation is also very high in all cases.

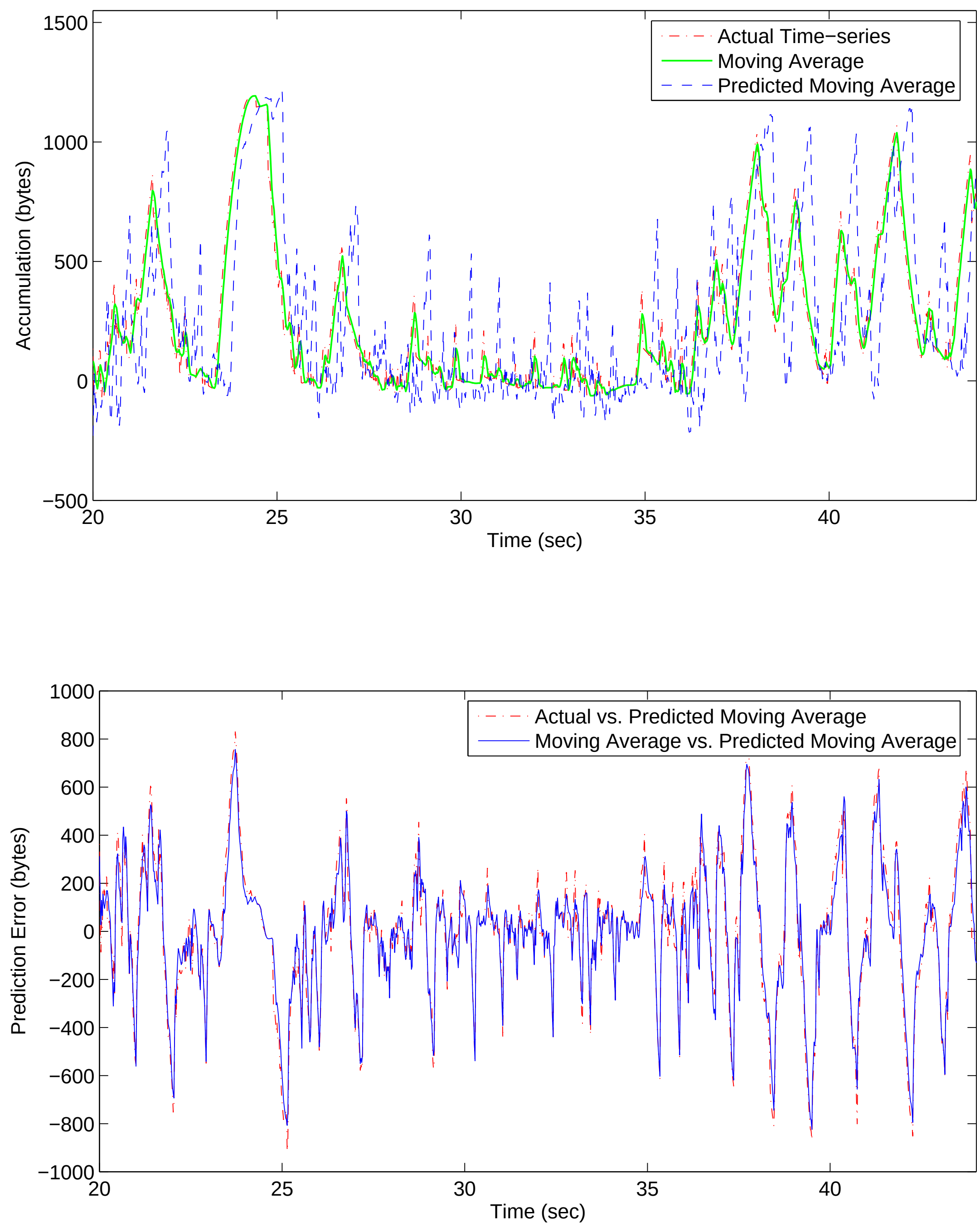


Fig. 32. 420 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the AR Model; Constant Send Rate of 30 Kbps with 20 ms Packet Inter-departure Time.

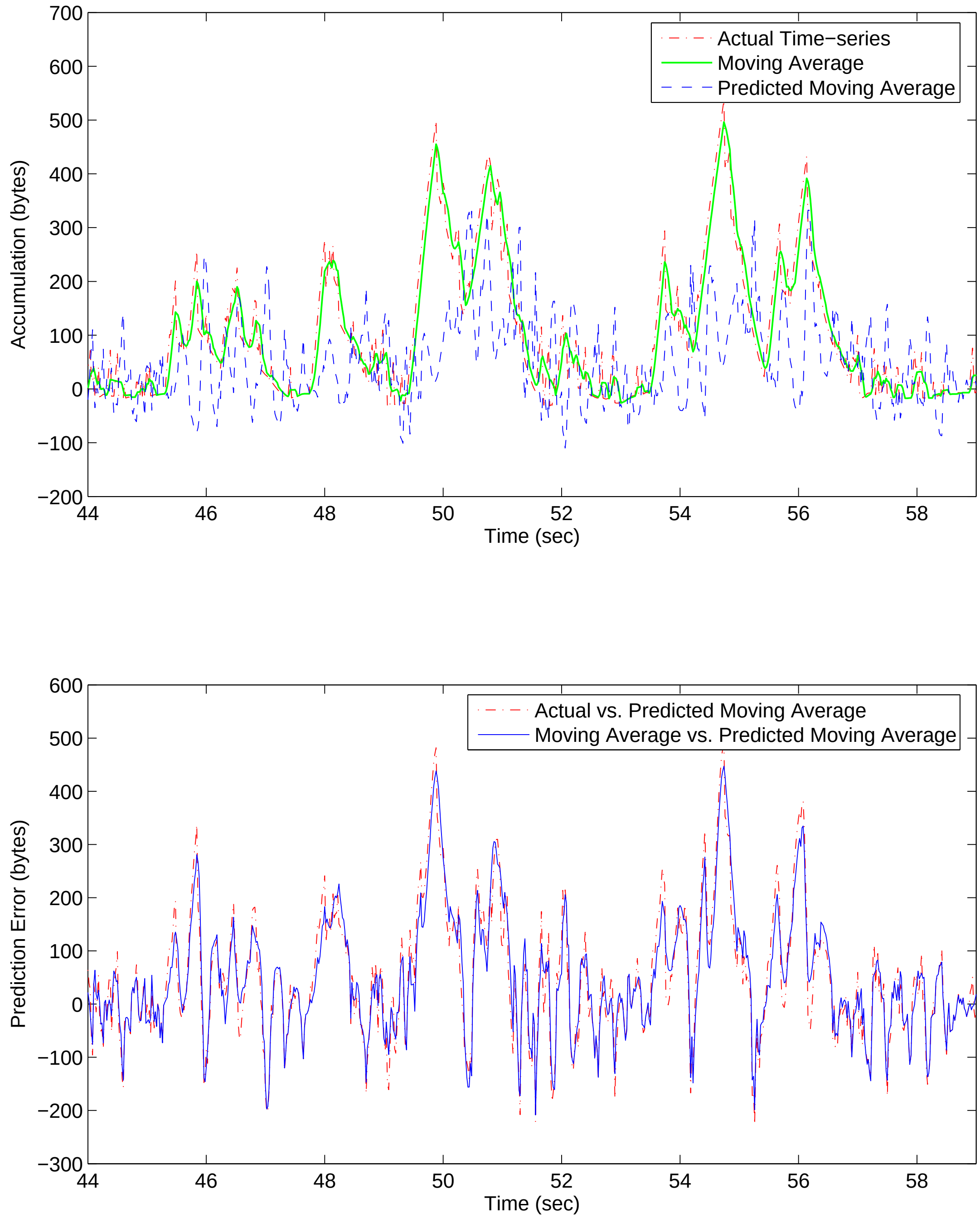
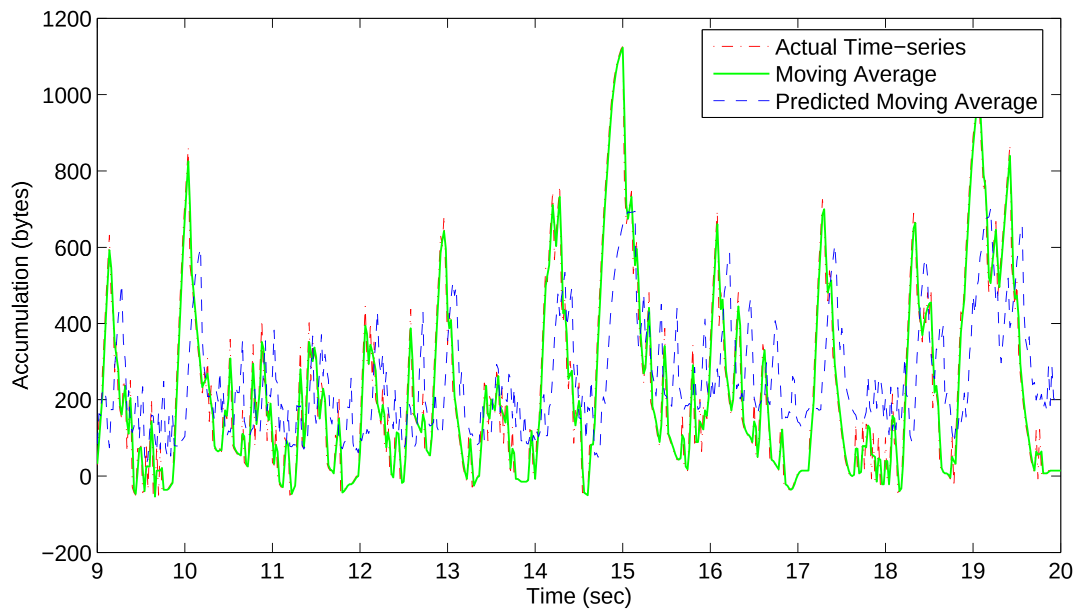


Fig. 33. 420 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the FMLP Model; Constant Send Rate of 10 Kbps with 20 ms Packet Inter-departure Time.



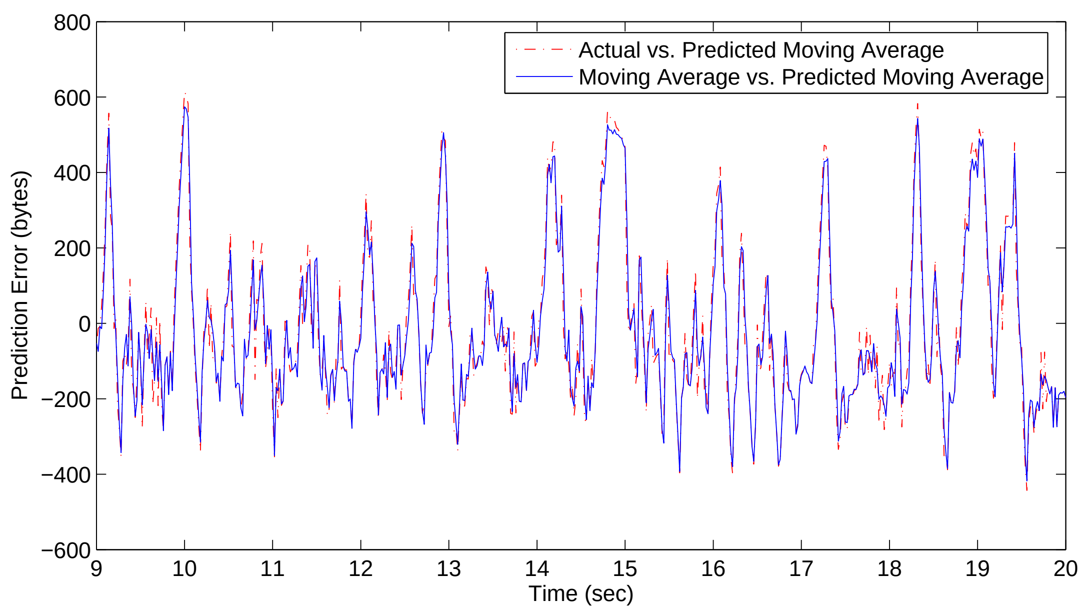


Fig. 34. 420 ms Ahead Prediction of Moving Average Accumulation on Node Pair 1 Using the ARMA Model; Constant Send Rate of 30 Kbpswith 60 ms Packet Inter-departure Time.

b. Comparison of Multi-Step-Ahead Predictor Performance

The results of the MSP using AR, ARMA and FMLP predictors are tabulated in this section. Each section show the performance evaluation results in terms of the performance indicator MSE.

120 ms-Ahead Prediction:

Tables XIV and XV show the performance evaluation results of the AR, ARMA and FMLP predictors for the various send rate test cases on node pair 1. Similarly, Tables XVI and XVII show the performance evaluation results of the AR, ARMA and FMLP predictors for the various send rate test cases on node pair 2.

Table XIV shows that AR, ARMA and FMLP results perform similar for various send rate cases with 20 ms inter-departure time of the send packets. It also shows that mean MSE for different seed-rate cases is similar. That means the developed predictors can perform well for different source send-rates. Table XV shows the 120 ms-ahead prediction results of the AR, ARMA and FMLP predictors for send rate cases having 60 ms inter-departure of the send packets. It also shows that the AR and ARMA models perform similarly while FMLP performs little worse in certain cases. It should also be observed that maximum MSE for FMLP model is higher than AR and ARMA models. Table XVI shows that the prediction results of the AR, ARMA and FMLP predictors for the various send rate cases on node pair 2 having 20 ms inter-departure of the send packets. Table XVII shows that the SSP results of the AR, ARMA and FMLP predictor for the various send rate cases having 60 ms inter-departure of the send packets. It should be observed here that the prediction results for flows having 20 ms packet inter-departure time is better than flows having 60 ms packet inter-departure time.

Table XIV. Comparative MSE Results of 120 ms-Ahead Predictions for Node Pair 1; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	4.75	1.93	7.42	4.86	1.84	7.54	3.42	2.08	6.99
30Kbps	5.05	4.14	5.92	5.19	3.94	6.50	5.40	2.94	7.85
40Kbps	4.28	3.69	5.11	4.33	3.82	4.98	4.94	3.15	7.44
50Kbps	4.48	2.94	5.05	4.43	2.99	5.21	5.79	3.55	7.08

Table XV. Comparative MSE Results of 120 ms-Ahead Predictions for Node Pair 1; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	6.12	2.45	7.76	6.32	2.43	10.89	6.80	3.48	14.50
30Kbps	5.89	2.48	11.18	6.35	2.78	13.06	6.18	2.61	8.15
40Kbps	6.55	3.39	8.17	6.95	2.17	8.27	8.75	5.34	13.50
50Kbps	6.46	2.14	8.36	7.30	3.08	10.28	8.57	6.33	12.01

Table XVI. Comparative MSE Results of 120 ms-Ahead Predictions for Node Pair 2; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	4.60	1.30	8.66	4.92	1.33	9.68	5.51	5.40	12.36
30Kbps	5.67	1.74	8.26	5.47	0.69	9.72	6.97	3.88	13.21
40Kbps	4.96	1.75	9.67	5.19	0.67	12.54	7.24	3.26	19.35
50Kbps	3.60	1.66	10.63	3.55	1.56	11.61	5.70	2.89	15.84

Table XVII. Comparative MSE Results of 120 ms-Ahead Predictions for Node Pair 2; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	5.42	2.49	9.53	6.12	2.54	10.04	6.55	2.93	13.24
30Kbps	8.87	2.53	10.03	9.89	2.94	11.93	10.48	3.58	11.79
40Kbps	7.55	1.65	11.19	7.58	1.85	12.18	9.54	1.98	13.63
50Kbps	8.98	2.77	12.15	8.83	2.85	13.16	9.73	2.13	14.30

240 ms-Ahead Prediction:

For the end-to-end single flows having 60 ms inter-departure time of the send packets, 240 ms ahead prediction means four step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of the send packets, it means twelve step-ahead prediction.

Tables XVIII and XIX show the performance evaluation results of the AR, ARMA and FMLP predictors for the various send rate test cases on node pair 1. Similarly, Tables XX and XXI show the performance evaluation results of the AR, ARMA and FMLP predictors for the various send rate test cases on node pair 2.

Table XVIII shows the AR, ARMA and FMLP results for various send rate cases with 20 ms inter-departure time of the send packets on node pair 1. Table XIX shows 240 ms-ahead prediction results of the AR, ARMA and FMLP predictors for send rate cases having 60 ms inter-departure of the send packets. Tables XVIII and XIX shows sudden increase of MSE when compared to the 120 ms-ahead prediction results. It indicates that prediction deteriorates faster when the prediction horizon is increased.

Table XX and XXI show the prediction results of the AR, ARMA and FMLP predictors for the various send rate cases with 20 and 60 ms inter-departure of the send packets, respectively. Though mean MSE for the node pair 1 and 2 are similar, maximum MSE for node pair 2 is much higher than node pair 1. It suggests that the prediction performance of the developed predictors is worse for node pair 2 than node pair 1. Here, it can also be observed from the tables that variation of MSE for data-sets collected during different time of the day is also more. It means that data-sets still contains lots of unmodeled dynamics.

Table XVIII. Comparative MSE Results of 240 ms-Ahead Predictions for Node Pair 1; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	12.05	5.80	20.36	12.16	5.93	23.81	10.59	7.56	22.01
30Kbps	13.71	10.69	23.22	14.42	10.36	23.92	11.09	7.78	32.57
40Kbps	12.43	10.94	13.05	13.10	11.33	15.38	18.79	10.89	32.96
50Kbps	11.64	8.97	14.35	11.97	9.85	16.18	22.97	17.92	23.84

Table XIX. Comparative MSE Results of 240 ms-Ahead Predictions for Node Pair 1; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	15.92	7.15	19.25	13.52	6.69	26.59	26.90	8.60	32.03
30Kbps	13.82	6.47	26.79	16.75	8.43	20.90	21.70	12.56	27.07
40Kbps	16.80	7.69	20.56	17.11	6.22	20.85	21.29	9.10	25.08
50Kbps	18.22	5.77	20.79	18.15	8.15	25.27	24.17	21.93	38.25

Table XX. Comparative MSE Results of 240 ms-Ahead Predictions for Node Pair 2; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	10.36	8.08	23.90	12.38	8.22	31.73	16.33	9.60	29.78
30Kbps	11.27	7.74	32.26	12.47	7.69	36.72	17.97	8.18	39.23
40Kbps	9.51	5.07	23.90	10.60	5.83	31.73	13.82	9.37	39.78
50Kbps	10.73	4.77	31.50	14.44	4.71	33.58	15.34	8.54	33.71

Table XXI. Comparative MSE Results of 240 ms-Ahead Predictions for Node Pair 2; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	11.08	7.71	38.87	14.34	8.54	37.32	18.62	12.25	38.46
30Kbps	22.23	8.71	39.73	23.85	8.46	47.51	25.34	8.47	50.59
40Kbps	17.10	6.25	32.46	19.03	7.47	44.54	29.11	7.79	52.57
50Kbps	17.21	7.90	33.34	19.10	8.78	42.77	27.32	11.66	42.82

420 ms-Ahead Prediction:

For the end-to-end single flows having 60 ms inter-departure time of the send packets, 420 ms ahead prediction means seven step-ahead prediction while for the end-to-end single flows having 20 ms inter-departure time of the send packets, it means twenty-one step-ahead prediction.

Table XXII. Comparative MSE Results of 420 ms-Ahead Predictions for Node Pair 1; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	25.98	15.75	49.29	29.30	17.44	51.96	30.81	21.96	57.70
30Kbps	32.38	23.50	35.08	38.61	24.40	39.42	39.42	29.17	51.25
40Kbps	30.59	26.90	35.77	36.75	31.71	40.09	32.20	23.82	53.52
50Kbps	27.33	24.12	36.70	31.31	29.85	47.13	33.68	31.46	45.33

Table XXIII. Comparative MSE Results of 420 ms-Ahead Predictions for Node Pair 1; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	35.82	17.32	44.37	33.19	15.91	50.12	46.90	18.60	52.07
30Kbps	32.18	14.12	57.51	40.91	19.21	59.10	35.77	12.56	57.07
40Kbps	38.45	16.63	47.55	41.07	15.87	51.83	54.27	16.10	55.08
50Kbps	38.80	13.35	50.28	41.83	18.47	55.94	44.17	31.94	58.25

Table XXIV. Comparative MSE Results of 420 ms-Ahead Predictions for Node Pair 2; Send Rate Cases Having 20 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	21.50	13.35	31.30	30.55	17.43	32.85	32.63	20.38	43.84
30Kbps	27.70	15.93	37.62	38.95	14.64	42.50	41.45	19.12	46.41
40Kbps	24.61	14.35	33.23	34.75	14.11	42.52	42.04	19.12	53.82
50Kbps	16.93	11.64	41.88	20.73	12.35	49.10	33.30	24.59	48.29

Table XXV. Comparative MSE Results of 420 ms-Ahead Predictions for Node Pair 2; Send Rate Cases Having 60 ms Packet Inter-departure Time.

Send Rate	AR			ARMA			FMLP		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	21.19	19.01	50.81	30.90	12.54	58.59	39.67	20.45	61.53
30Kbps	37.64	18.40	61.22	42.75	18.46	57.51	44.24	18.47	72.33
40Kbps	31.51	16.20	57.47	36.79	20.82	62.97	56.37	18.37	75.06
50Kbps	32.93	18.74	66.25	38.50	22.41	64.11	59.15	21.99	70.88

Table XXII and XXIII shows the AR, ARMA and FMLP results for various send rate cases with 20 and 60 ms inter-departure time of the send packets on node pair 1. Table XXIV and XXV show the prediction results of the AR, ARMA and FMLP predictors for the various send rate cases with 20 and 60 ms inter-departure of the send packets on node pair 2, respectively. They show further increase of MSE from 240 ms-ahead prediction results. From the tables, it can be seen that AR models performs best among developed models and FMLP models perform worst.

It should be also noted that maximum MSE in case of AR model is the least which further indicates that AR models perform best among the developed models when prediction horizon is increased. It should be observed that maximum MSE is much higher for flows having 60 ms packet inter-departure time. By noting the difference between minimum and maximum MSE , it can be derived that developed predictors fail to capture important dynamics of the system under varying cross-traffic conditions.

D. Path-Independent Predictors

Here, path-independent predictors means that the predictor is developed for a particular pair of source and destination nodes and its performance is then evaluated for different pair of source and destination nodes. The motivation behind developing path-independent predictors is to check the feasibility of developing generic empirical model that can be used for any source and destination pair.

1. Description of Training and Validation Data Sets

Data-sets used in this section is measured from the PlanetLab network. As present research is more interested in a congested network, data-sets having than 3% losses are only used for modeling and testing of models. That means it is assumed that the network is congested if the total loss in the collected data-sets is more than 3%. All data-sets used in section have 60 ms inter-departure time of the send packets.

Three different sets of source and destination pair are selected and various linear and non-linear predictors are individually developed for each source and destination pair. Table XXVI shows three pair of source and destination nodes used in present section. It also shows the name of models developed for three source-destination pairs. Henceforth, Ucsd3-Niml node pair will be referred as node pair 1, Niml-seattle3 node pair will be referred as node pair 2 and Niml-nbgisp3 node pair will be referred as node pair 3. Details of the data-collection process have been explained in Chapter III.

Table XXVI. Source and Destination Nodes on PlanetLab Used for Data Collection.

Soure Node	Destination Node	Developed models
Ucsd3(PlanetLab)	Niml (TAMU)	AR 1,ARMA 1,FMLP 1
Niml (TAMU)	Seattle3(PlanetLab)	AR 2,ARMA 2,FMLP 2
Niml (TAMU)	nbgisp3(PlanetLab)	AR 3,ARMA 3,FMLP 3

In all cases, the linear and non-linear predictors are developed at source-rate of 30 Kbps. Performance of all the developed predictors are tested on the data-sets collected from the node pair 1. Performance of the developed models is then evaluated for different source send-rate between 20 Kbps to 50 Kbps. Here, source send-rate is varied by changing the packet-size of send packets. It is important to note that the inter-departure time and the packet-size of the sent flow are constant for a particular session. For every source-send rate, Performance of the developed predictors are validated for 5 data-sets collected during different time of the day. This has been done to gauge the predictor performance under varying cross-traffic conditions.

The network accumulation for each traces is computed by periodically calculating cumulative send and arrival flow at the source and the destination. The time interval used for measuring cumulative flows is equal to the inter-departure time of send packets. The data-sets is then processed before using for modelling and testing of the predictive models. Processing of the data-sets includes two steps. First, the trend is removed from the total accumulation to calculate present accumulation in the network. And then time-series of the moving average of present accumulation is calculated for system identification purpose. Here, the trend is dynamically calculated by adding mean slope of last 1 second window to the current value of the trend. The moving average window is set as 120 ms and the window is moved by one sample i.e. window is moved by 60 ms.

2. Development of Linear and Non-linear Predictors

The next step is to use system identification techniques to obtain the best empirical model. Here, three different sets of linear and non-linear predictors for are developed and tested for 60 ms packet inter-departure time of the send packets. In all cases, the linear and non-linear predictors are developed at 30 Kbps source send-rate.

For Node pair 1, after various permutations and combinations, an AR predictor with model structure {17} and ARMA with model structure {17 3} give the best fit for the training data-set. Those models will be referred as AR 1 and ARMA 1 from now on. After extensive search over several possible FMLP architectures, FMLP model structure {11 3 1} which translates into 11 input layer nodes, 3 hidden layer nodes and 1 output layer is found to be the best model-structure for the training data-set. Henceforth, this model will be referred as FMLP 1.

Similar process is performed for the Node pair. An AR predictor with model structure {12} and ARMA with model structure {16 5} have been found to be most suitable for the prediction. Those models will be referred as AR 2 and ARMA 2 from now on. The most suitable FMLP model structure for the training data-set is {11 3 1}. It will be referred as FMLP 2. Similarly for the node pair 3, An AR predictor with model structure {19} and ARMA with model structure {22 7} have been found to be most suitable for the prediction. Those models will be referred as AR 3 and ARMA 3 from now on. The most suitable FMLP model structure for the training data-sets is {15 3 1}. It will be referred as FMLP 3.

It is important to note that training data-set are different for each set of predictors. During the training process the performance of the predictor is determined using the mean square error of the signal.

3. Single-Step Ahead Prediction

A single step-ahead prediction is a first step in evaluating the performance of any developed predictor. SSP in following cases means 60 ms ahead prediction.

a. Performance Evaluation of Single-Step-Ahead Predictors

Figure 35 shows the SSP of moving average accumulation using the AR models for a constant send rate of 20 Kbps. It can be seen from the figure that model AR 1 and AR 2 perform similarly for the SSP. It also shows that AR 1 and AR 2 can capture the accumulation peaks accurately and can capture important dynamics of the network. Figure 36 shows the SSP of moving average accumulation using the ARMA models for a constant send rate of 30 Kbps. It shows that ARMA models perform accurately and similar in this case too.

Figure 37 shows the SSP of moving average accumulation using the FMLP models for a constant send rate of 50 Kbps. From the figure, it can be deducted that FMLP

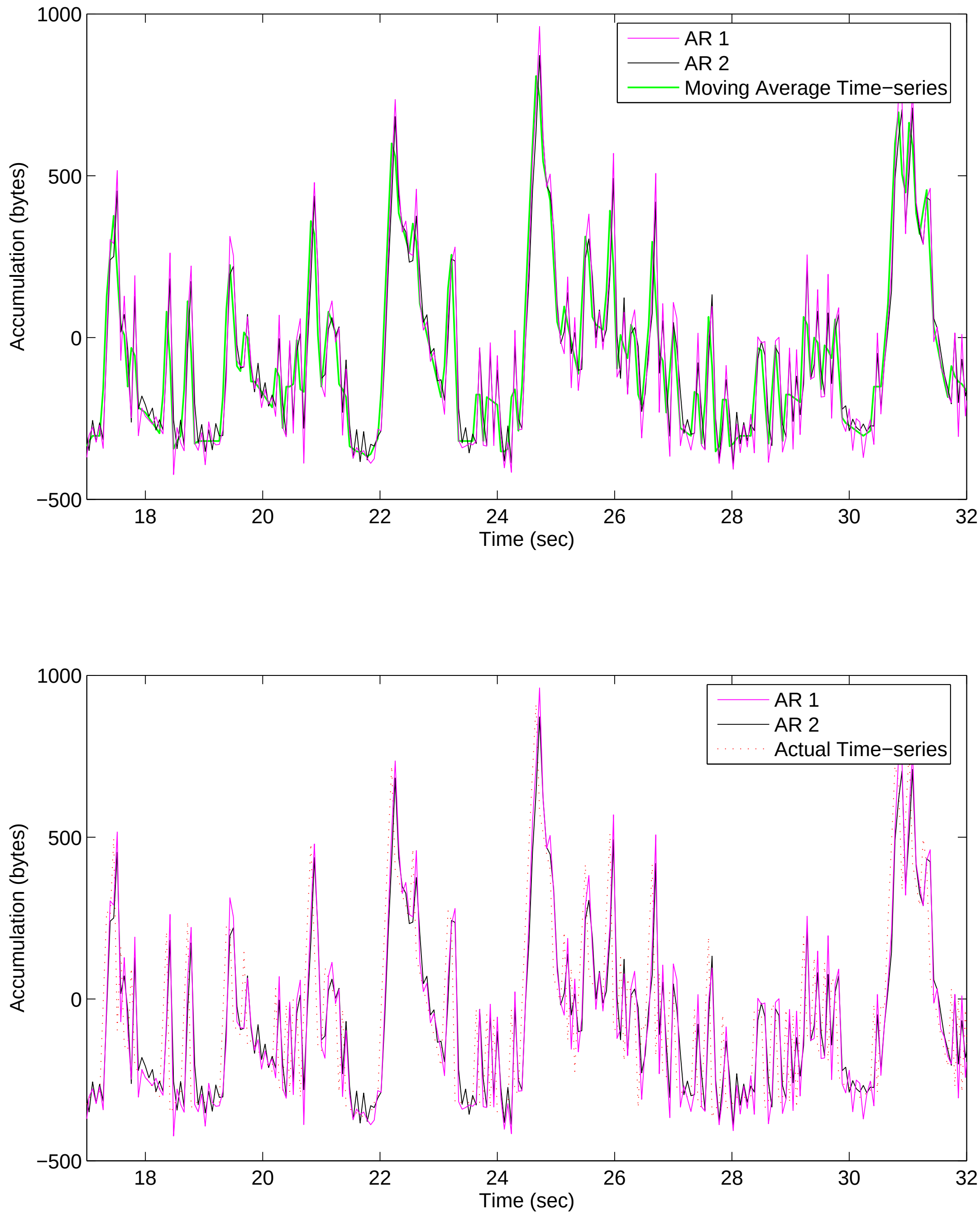


Fig. 35. Single-Step-Ahead Prediction of Moving Average Accumulation Using the AR Model for a Constant Send Rate of 20 Kbps.

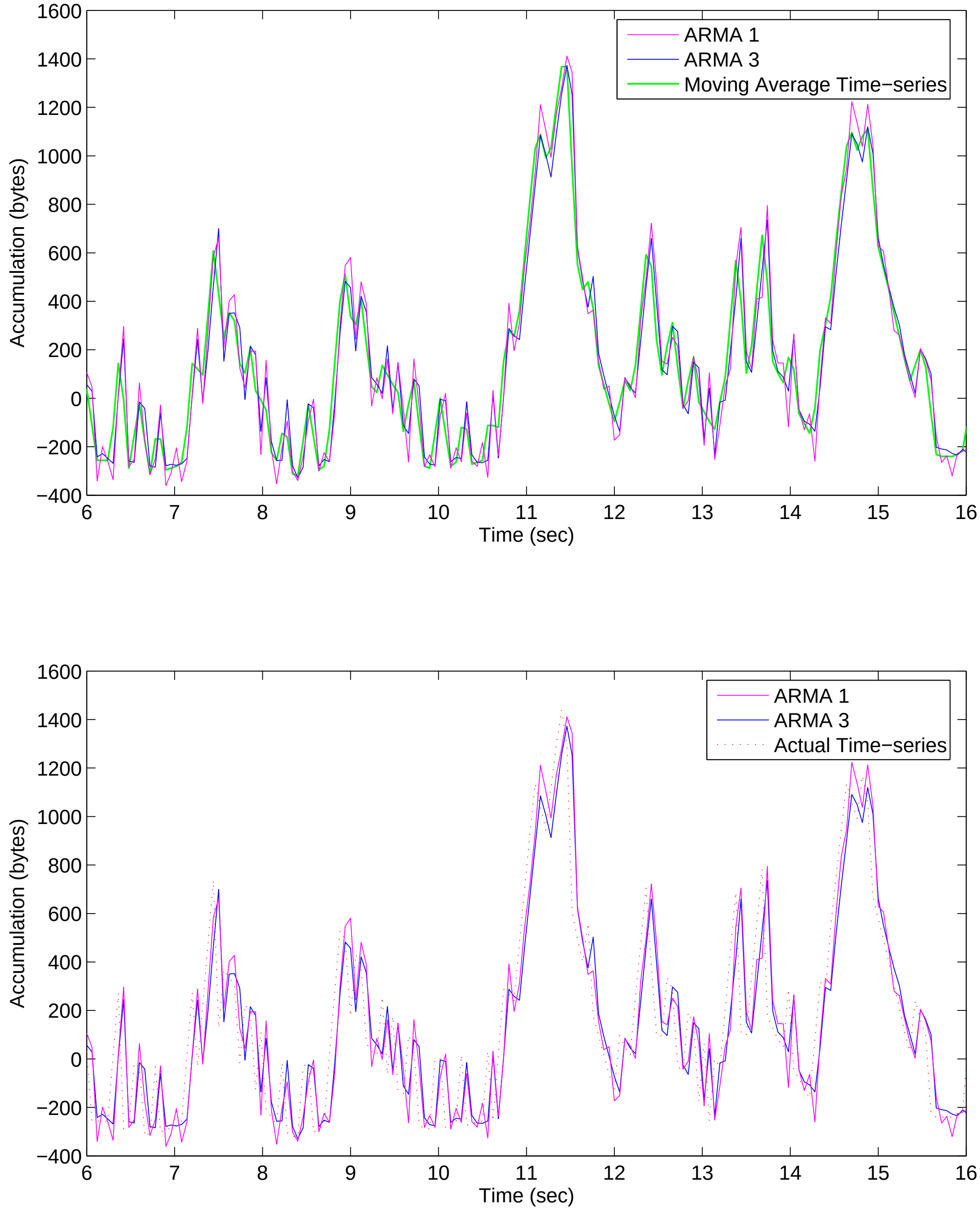


Fig. 36. Single-Step-Ahead Prediction of Moving Average Accumulation Using the ARMA Model for a Constant Send Rate of 30 Kbps.

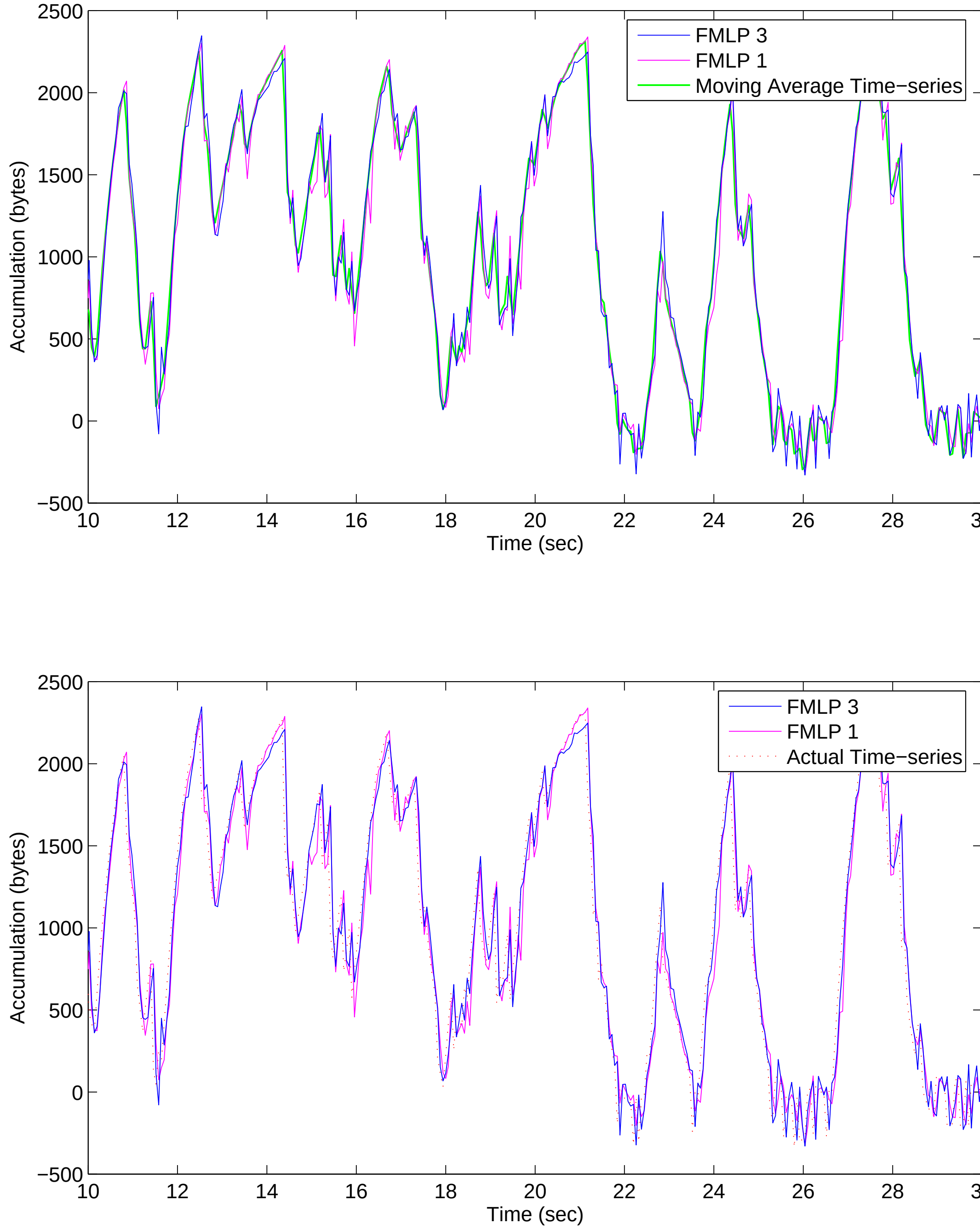


Fig. 37. Single-Step-Ahead Prediction of Moving Average Accumulation Using the FMLP Model for a Constant Send Rate of 50 Kbps.

2 model does not perform as good as FMLP 1 model. The figures show that the predictors developed for different end-to-end path perform similar for the SSP of the actual accumulation.

b. Comparison of Single-Step-Ahead Predictor Performance

The results of the SSP using AR, ARMA and FMLP predictors are tabulated in this section. Following tables show the performance evaluation results in terms of the performance indicator MSE. As discussed earlier, 5 data-sets are collected for every source send-rate and tables show mean, minimum and maximum value of MSE for all send-rate cases.

Table XXVII. Comparative MSE Results of Single-Step-Ahead Predictions for AR Models.

Send Rate	AR 1			AR 2			AR 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	2.48	1.01	3.37	3.40	1.54	4.85	3.44	1.47	4.97
30Kbps	1.99	0.96	3.17	2.35	1.25	5.63	2.33	1.16	5.67
40Kbps	2.77	1.37	3.65	3.21	1.78	3.96	3.20	1.72	4.03
50Kbps	2.65	0.84	3.71	3.10	1.15	4.01	3.13	1.06	4.06

Table XXVII shows the performance results of AR models for different source send-rate. It can be seen from the table that the performance of AR 1, AR 2 and AR 3 models is similar. Table XXVIII shows the performance results of ARMA models at different source send-rate. It can be seen from the table that the performance of ARMA 1 , ARMA 2 and ARMA 3 models are also similar. It should be observed that maximum MSE for all three developed models are also quite less, which indicates that

Table XXVIII. Comparative MSE Results of Single-Step-Ahead Predictions for ARMA Models.

Send Rate	ARMA 1			ARMA 2			ARMA 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	1.81	0.94	5.26	3.20	1.63	4.55	3.25	1.45	4.64
30Kbps	2.54	1.31	3.54	2.27	1.37	5.30	2.20	1.16	5.37
40Kbps	2.46	0.84	3.61	3.01	1.74	3.74	3.02	1.69	3.79
50Kbps	3.13	1.26	4.4	2.71	1.25	3.75	2.95	1.05	3.75

Table XXIX. Comparative MSE Results of Single-Step-Ahead Predictions for FMLP Models.

Send Rate	FMLP 1			FMLP 2			FMLP 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	2.04	1.07	5.56	7.94	5.62	9.41	8.10	5.35	9.56
30Kbps	2.64	1.22	3.51	4.67	3.71	8.08	2.41	1.26	5.50
40Kbps	2.84	1.17	3.91	6.61	5.17	7.58	3.01	1.66	4.46
50Kbps	3.17	1.69	4.67	6.80	5.37	8.08	3.15	0.98	4.10

the ARMA models perform accurately under varying cross-traffic conditions. Table XXIX shows the performance results of FMLP models at different source send-rate. It should be observed from the table that FMLP 1 and FMLP 3 models perform similar while worse FMLP 2 model performs worse than them.

4. Multi-Step Ahead Prediction

Present section explores the multi-step-ahead prediction of the developed linear and non-linear predictors. To be useful for a congestion control/avoidance algorithms, generic predictor must be able to predict end-to-end single flow characteristics well ahead of time.

a. Performance Evaluation of Multi-Step-Ahead Predictors

The send-rate test cases used for evaluating the MSP predictors are same as the send-rate cases used for evaluating SSP predictors. This will be helpful in comparing various time-step-ahead predictors on a common scale. Multi-step ahead prediction contains three sections: 120 ms-ahead prediction, 240-ms ahead prediction and 420 ms-ahead prediction.

120 ms-Ahead Prediction:

In present section, 120 ms ahead prediction means two step-ahead prediction. Figure 38 shows the 120 ms-ahead prediction of moving average accumulation using the AR models for a constant send rate of 40 Kbps. It can be seen from the figure that the developed models perform accurately but AR 1 model performs slightly better than AR 2 model.

Figure 39 shows the 120 ms-ahead prediction of moving average accumulation using the ARMA models for a constant send rate of 30 Kbps. Figure 40 shows the

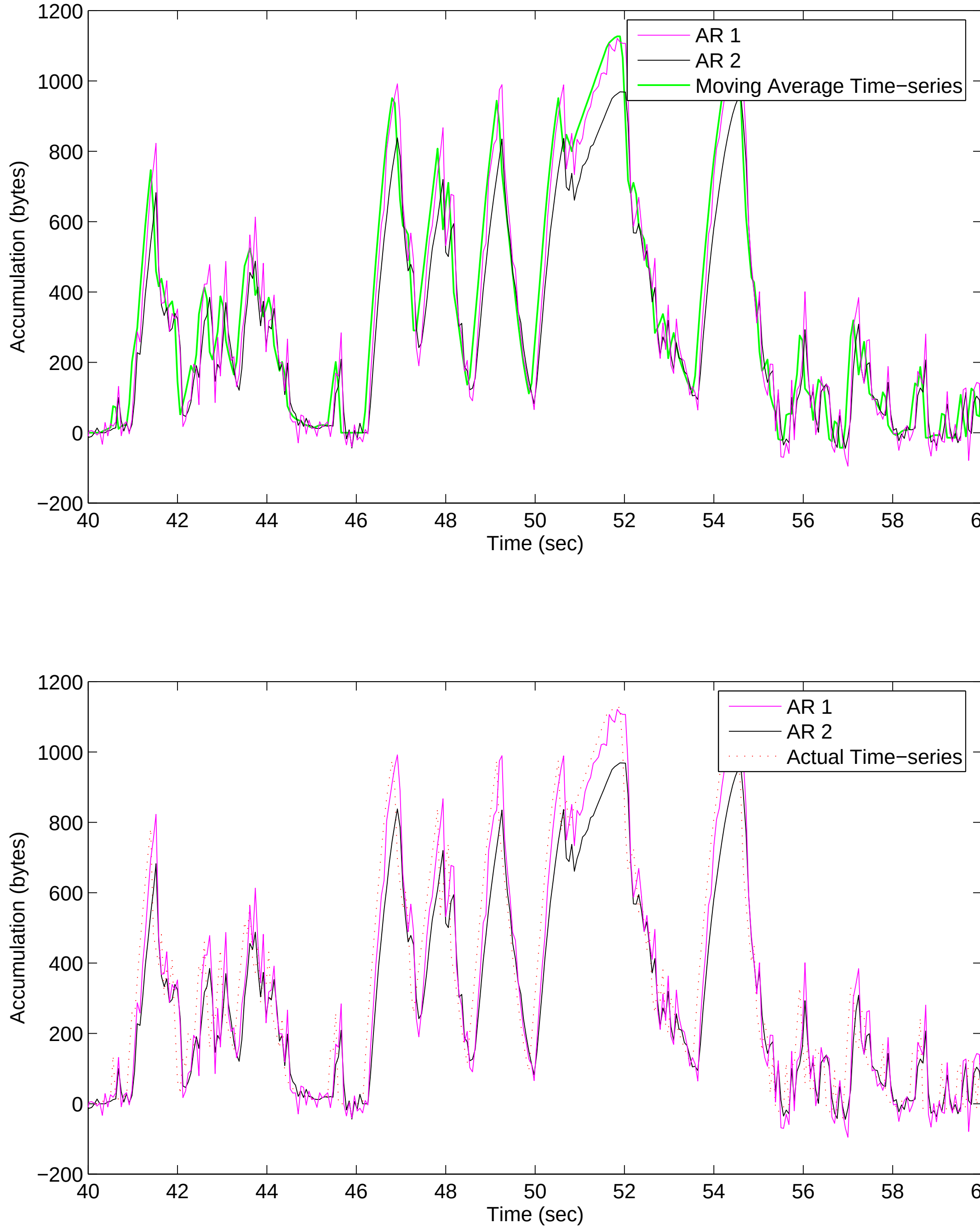
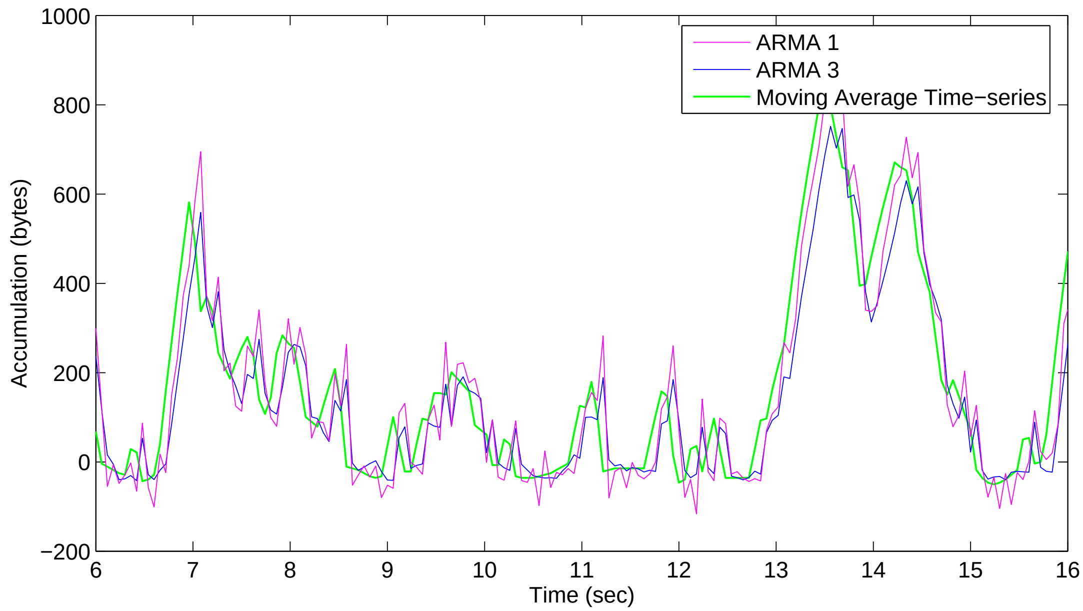


Fig. 38. 120 ms Ahead Prediction of Moving Average Accumulation Using the AR Model for a Constant Send Rate of 40 Kbps.



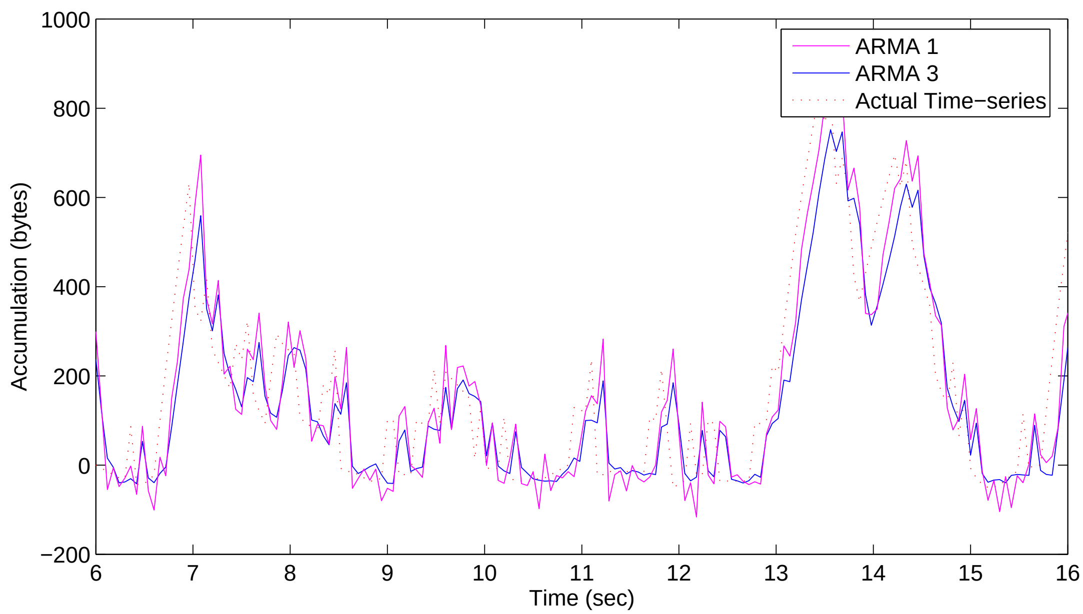


Fig. 39. 120 ms Ahead Prediction of Moving Average Accumulation Using the ARMA Model for a Constant Send Rate of 30 Kbps.

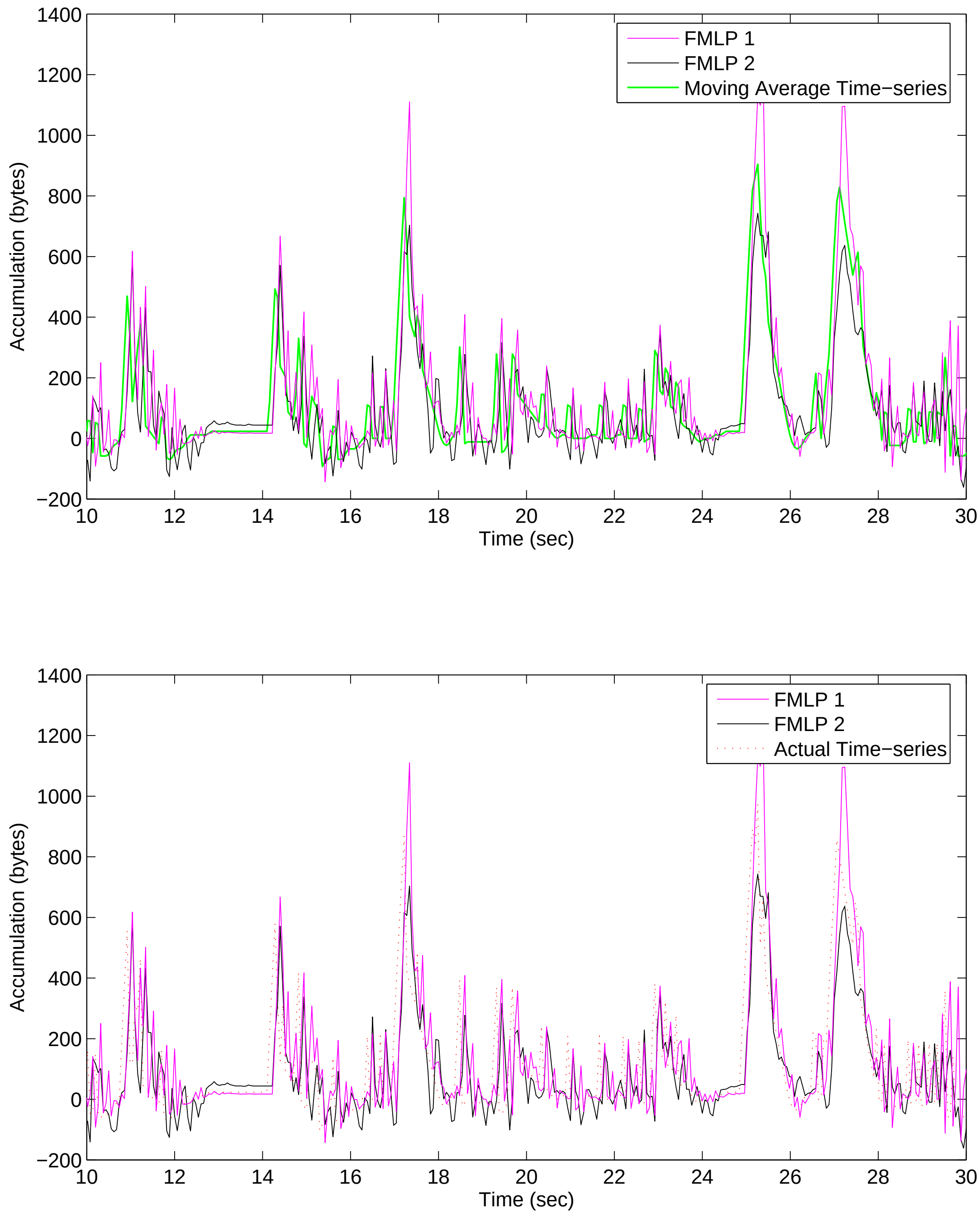


Fig. 40. 120 ms Ahead Prediction of Moving Average Accumulation Using the FMLP Model for a Constant Send Rate of 20 Kbps.

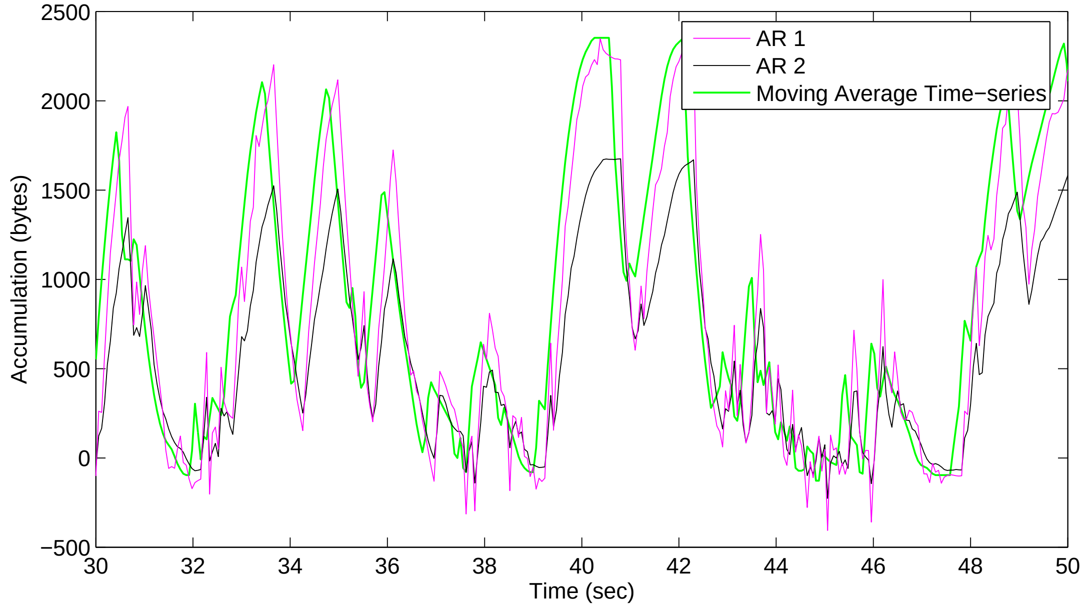
SSP of moving average accumulation using the FMLP models for a constant send rate of 20 Kbps. The figures show that the predictors developed for node pair 1 performs best among the developed models but the performance of the models developed for node pair 2 and 3 is also good.

240 ms-Ahead Prediction:

In the present section, 240 ms-ahead prediction means four-step ahead prediction. Figure 41 shows the 240 ms-ahead prediction of moving average accumulation using the AR models for a constant send rate of 20 Kbps. It can be seen from the figure that AR1 model performs better than AR 2 model. This is understandable as AR 1 is developed for this particular end-to-end path while AR 2 is developed for different end-to-end path. It is also important to observe that the time-shift observed between the actual accumulation and the predicted moving average accumulation remains almost same for both predictors.

Figure 42 shows the 240 ms-ahead prediction of moving average accumulation using the ARMA models for a constant send rate of 40 Kbps. This figure also shows performance of the ARMA 1 and ARMA 3 model. Figure shows that ARMA 1 performs better than ARMA 3 model.

It is important to note that as the prediction horizon is increased, the performance of the predictors developed on other end-to-end path deteriorates faster than the predictors developed on that particular end-to-end path. That means that predictors developed on other end-to-end paths may not capture certain specific dynamics of this particular end-to-end path. It can also be seen from the figures that developed models perform satisfactorily for 240 ms prediction horizon. It should be also noted that time-shift between predicted and actual signal is almost similar for all the developed predictors.



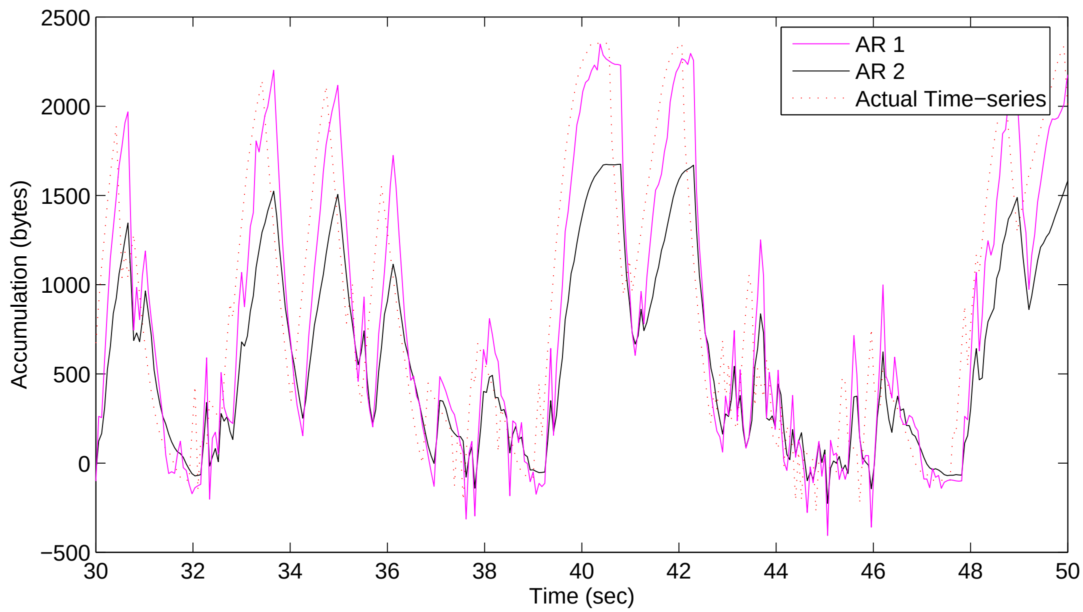


Fig. 41. 240 ms Ahead Prediction of Moving Average Accumulation Using the AR Model for a Constant Send Rate of 20 Kbps.

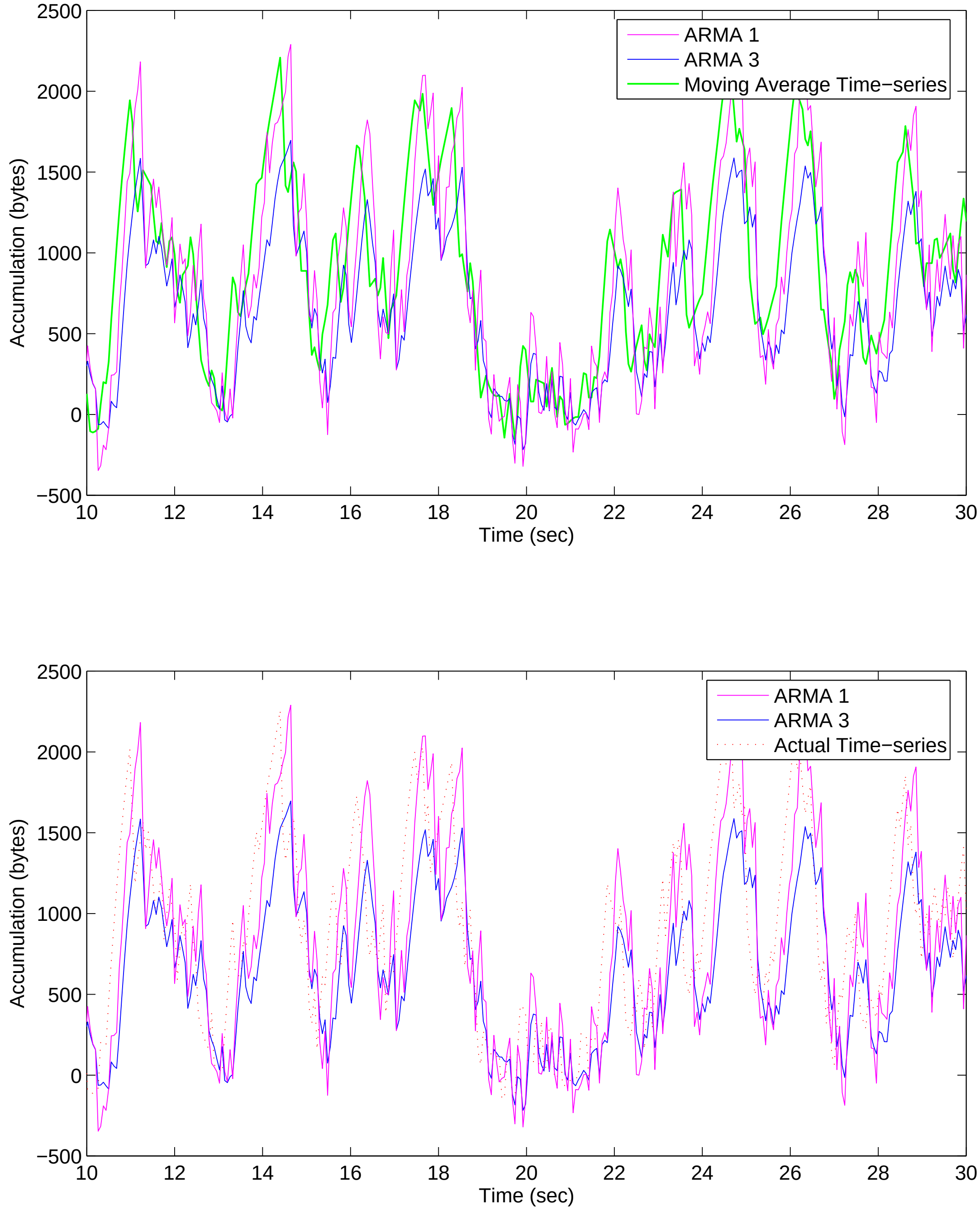


Fig. 42. 240 ms Ahead Prediction of Moving Average Accumulation Using the ARMA Model for a Constant Send Rate of 40 Kbps.

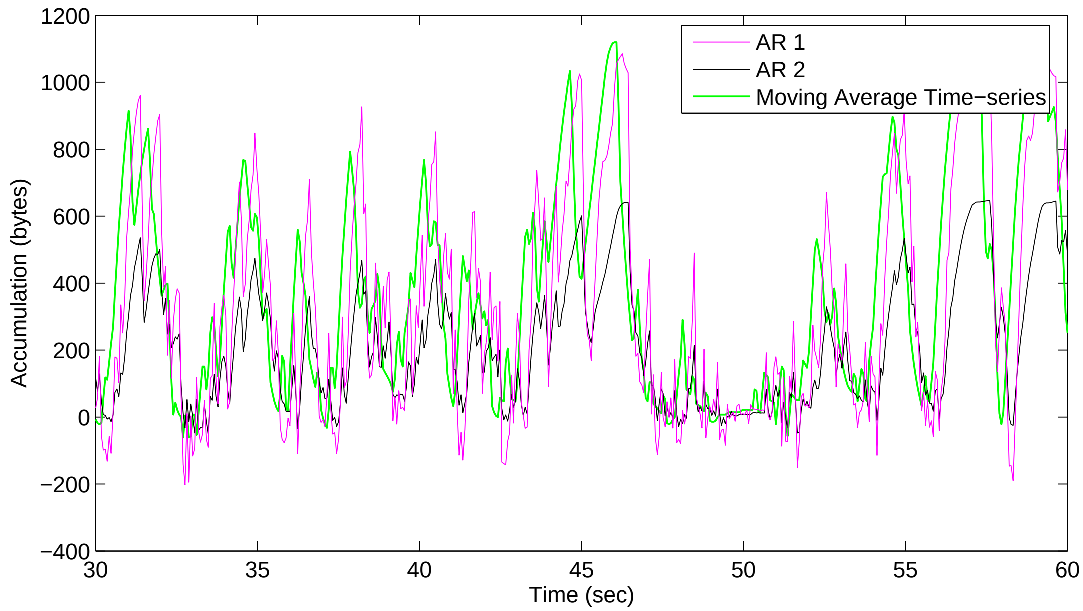
420 ms-Ahead Prediction:

Here, 420 ms ahead prediction means seven-step ahead prediction. Figure 43 shows the 420 ms-ahead prediction of moving average accumulation using the AR models for a constant send rate of 20 Kbps. It show the performance of the AR1 model and AR 2 model for 420 ms-ahead prediction. Figure shows that AR 1 model performs better than AR 2 model. It means that when the prediction horizon is increased, deterioration of the AR 2 model performance is much faster than AR 1 model.

Figure 44 shows the 420 ms-ahead prediction of moving average accumulation using the ARMA models for a constant send rate of 50 Kbps. This figure also shows that ARMA 1 model performs much better than ARMA 2 model. It can be seen in the figures that the models developed on the same end-to-end path performs best among developed models.

It can be easily seen that all the developed models, including the models developed for this particular path, fails to perform well for 420 ms ahead prediction. In figures, missing of certain spikes is easily noticeable. It is also seen that prediction of spikes is sometimes only done after entire spike is gone. As this predictor is intended to be used in real time, timeliness of the prediction is as important as the accuracy of the predictor.

In general, predictors developed for this particular end-to-end path performs better than the predictors developed for different end-to-end paths. This suggests that different end-to-end path has little different end-to-end flow dynamics. It also shows that when prediction horizon is increased the performance of the predictors developed on this particular path is better than the predictors developed for different end-to-end paths.



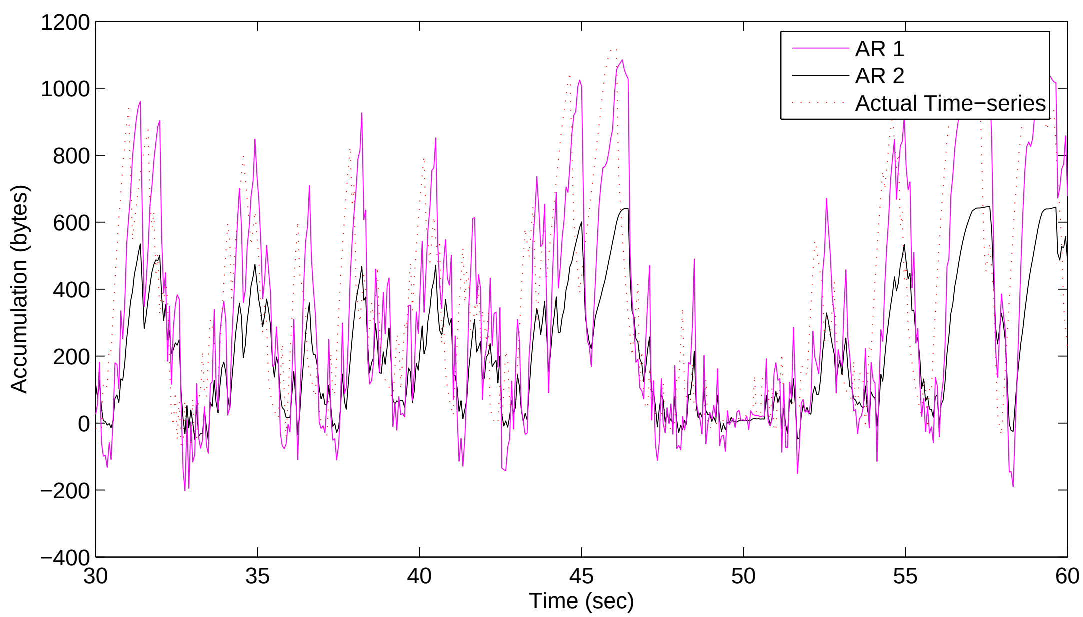
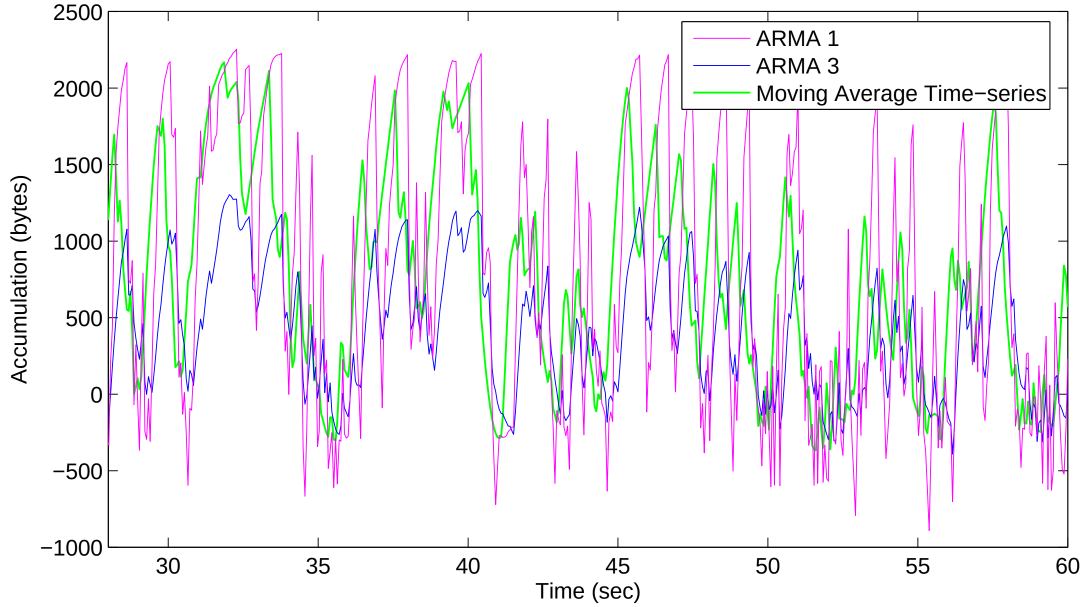


Fig. 43. 420 ms Ahead Prediction of Moving Average Accumulation Using the AR Model for a Constant Send Rate of 20 Kbps.



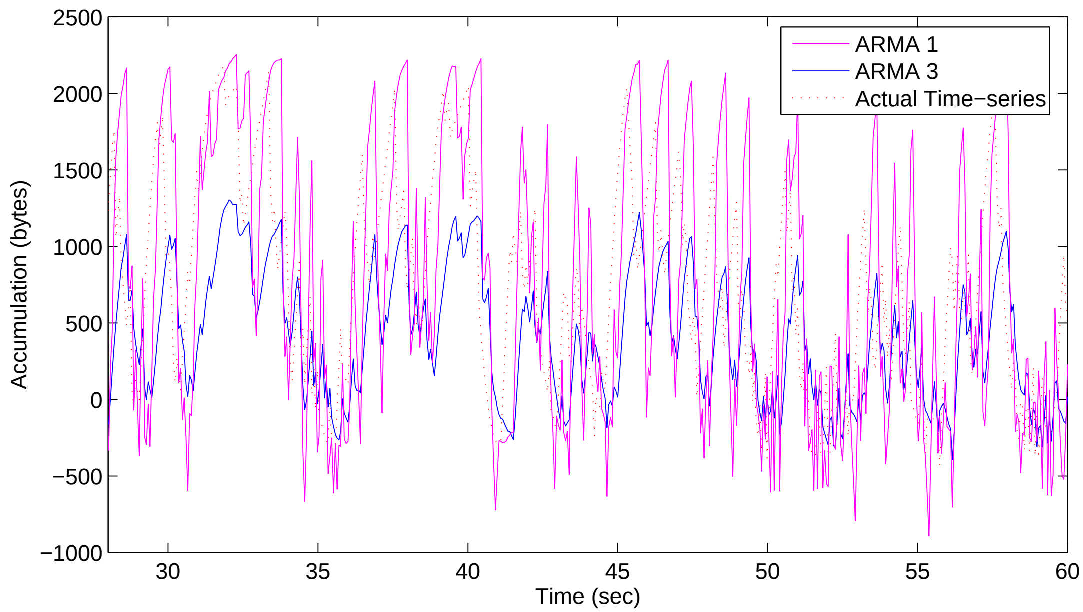


Fig. 44. 420 ms Ahead Prediction of Moving Average Accumulation Using the ARMA Model for a Constant Send Rate of 50 Kbps.

b. Comparison of Multi-Step-Ahead Predictor Performance

The results of the MSP using AR, ARMA and FMLP predictors are tabulated in this section. Each section show the performance evaluation results in terms of the performance indicator MSE.

120 ms-Ahead Prediction:

Here, 120 ms ahead prediction means two step-ahead prediction. Table XXX shows the performance results of AR models for different source send-rates. It can be seen from the table that the performance of AR 1 is accurate while AR 2 and AR 3 model perform slightly worse than AR 1 model.

Table XXXI shows the performance results of ARMA models at different source send-rate. It can be seen from the table that the performance of ARMA 1 is better than ARMA 2 and ARMA 3 models. It should be observed that maximum MSE for all three developed models are similar.

Table XXXII shows the performance results of FMLP models for different source send-rates. It should be observed from the table that FMLP 1 and FMLP 3 models perform similar while worse FMLP 2 model performs very bad. It is important to observe that maximum MSE of FMLP 2 model in some cases are extremely high. That indicated that FMLP 2 models perform very bad under varying cross-traffic conditions. This also true for FMLP 3 model.

It can be seen from the tables that AR models perform better in general than ARMA and FMLP models. Also, AR models developed for different end-to-end paths perform more accurately than ARMA and FMLP model developed for different end-to-end paths.

Table XXX. Comparative MSE Results of 120 ms-Ahead Predictions for AR Models.

Send Rate	AR 1			AR 2			AR 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	6.12	2.45	7.76	8.89	4.60	11.94	8.46	3.76	11.62
30Kbps	5.89	2.48	11.18	7.04	4.09	12.68	6.39	3.21	12.23
40Kbps	6.55	3.39	8.17	8.72	4.06	8.97	8.05	4.14	9.52
50Kbps	6.46	2.14	8.36	8.38	3.95	9.96	8.33	3.04	9.45

Table XXXI. Comparative MSE Results of 120 ms-Ahead Predictions for ARMA Models.

Send Rate	ARMA 1			ARMA 2			ARMA 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	6.32	2.43	10.89	9.21	6.07	11.86	8.55	4.38	11.32
30Kbps	6.35	2.78	13.06	7.68	5.97	12.18	6.64	3.86	11.99
40Kbps	6.27	2.17	8.27	8.91	6.60	10.12	8.04	4.67	9.53
50Kbps	7.30	3.08	10.28	8.15	5.63	10.18	7.86	3.57	9.52

Table XXXII. Comparative MSE Results of 120 ms-Ahead Predictions for FMLP Models.

Send Rate	FMLP 1			FMLP 2			FMLP 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	6.80	3.48	14.50	14.65	6.39	37.89	9.01	7.43	19.74
30Kbps	6.18	2.61	8.15	17.40	13.58	23.69	7.72	4.05	13.35
40Kbps	7.35	5.34	13.50	8.15	7.34	24.91	6.61	4.20	28.14
50Kbps	8.57	6.33	12.01	13.50	12.85	29.87	9.34	2.87	29.93

240 ms-Ahead Prediction:

Here, 240 ms ahead prediction means four step-ahead prediction. Table XXXIII shows the performance results of AR models at different source send-rates. It can be seen from the table that the deterioration of the prediction results of AR2 and AR3 model is much faster than the prediction results of AR1 model. It should be noted that AR 1 and AR 3 models perform comparable while AR 2 does not perform that accurate.

Table XXXIV shows the performance results of ARMA models at different source send-rate. It can be seen from the table that the performance of ARMA 1 model is better than ARMA 2 and ARMA 3 models. It should be observed maximum MSE for ARMA 2 and ARMA 3 models are much higher than ARMA model.

Table XXXV shows the performance results of FMLP models for different source send-rates. It should be observed from the table that FMLP 1 model performs better than FMLP 2 and FMLP 3 models. The performance of FMLP 3 model is still acceptable but FMLP 2 model performs extremely bad. It is important to observe that maximum MSE of FMLP 2 model in some cases are extremely high. It indicates that the FMLP 2 model perform very bad under varying cross-traffic conditions.

Table XXXIII. Comparative MSE Results of 240 ms-Ahead Predictions for AR Models

Send Rate	AR 1			AR 2			AR 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	15.92	7.15	19.25	23.07	13.03	28.68	20.60	9.35	25.90
30Kbps	13.82	6.47	26.79	19.39	11.96	30.01	16.23	8.16	27.75
40Kbps	16.80	7.69	20.56	22.72	13.70	25.02	19.26	9.88	22.66
50Kbps	18.22	5.77	20.66	20.79	12.92	24.37	19.77	10.13	22.15

Table XXXIV. Comparative MSE Results of 240 ms-Ahead Predictions for ARMA Models.

Send Rate	ARMA 1			ARMA 2			ARMA 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	13.52	6.69	26.59	27.71	20.46	31.10	20.87	12.90	26.80
30Kbps	16.75	8.43	20.90	25.39	22.29	31.34	18.68	11.76	28.60
40Kbps	17.11	6.22	20.85	26.82	12.70	28.68	21.17	12.98	24.10
50Kbps	18.15	8.15	25.27	25.55	20.84	28.66	20.87	11.3	24.5

Table XXXV. Comparative MSE Results of 240 ms-Ahead Predictions for FMLP Models.

Send Rate	FMLP 1			FMLP 2			FMLP 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	26.90	8.60	32.03	38.37	28.43	46.89	28.47	23.40	49.92
30Kbps	21.70	12.56	27.07	34.57	25.59	45.29	23.37	12.91	35.65
40Kbps	21.29	9.10	25.08	40.21	31.29	43.96	15.42	10.20	26.82
50Kbps	24.17	11.93	28.25	39.36	31.45	51.24	21.49	7.74	34.98

420 ms-Ahead Prediction:

In present case, 420 ms-ahead prediction means seven-step-ahead prediction. Table XXXVI shows the performance results of AR models at different source send-rates. It can be seen from the table that the deterioration of the prediction results of AR1 and AR3 models perform equivalent while AR 2 model performs extremely bad. It should be noted here that maximum MSE for all the AR models are very high. That indicates that all the developed AR model fails capture end-to-end flow dynamics for 420 ms ahead prediction.

Table XXXVII shows the performance results of ARMA models at different source send-rate. It can be seen from the table that the performance of ARMA 1 model is better than ARMA 2 and ARMA 3 models. It should be observed maximum MSE for ARMA 2 and ARMA 3 models are much higher than ARMA 1 model. It means ARMA2 and ARMA 3 models does not perform consistently under varying cross-traffic conditions.

Table XXXVIII shows the performance of FMLP models for different source send-rates. It should be observed from the table that FMLP 1 model performs better

Table XXXVI. Comparative MSE Results of 420 ms-Ahead Predictions for AR Models.

Send Rate	AR 1			AR 2			AR 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	35.82	17.32	44.37	49.21	28.96	55.90	42.64	19.04	50.60
30Kbps	32.18	14.12	57.51	41.48	27.47	59.60	33.52	17.33	54.03
40Kbps	38.45	16.63	47.55	47.20	31.27	51.30	39.36	20.71	45.62
50Kbps	38.80	13.35	50.28	44.20	28.90	51.20	37.70	18.10	48.16

Table XXXVII. Comparative MSE Results of 420 ms-Ahead Predictions for ARMA Models.

Send Rate	ARMA 1			ARMA 2			ARMA 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	33.19	15.91	50.12	55.90	33.29	62.94	47.57	18.42	63.42
30Kbps	40.91	19.22	59.10	57.40	34.40	62.87	40.16	17.46	56.02
40Kbps	41.07	15.87	51.83	58.80	34.60	61.66	44.76	19.25	49.85
50Kbps	41.83	18.47	55.94	57.80	23.40	60.01	43.51	27.17	51.93

Table XXXVIII. Comparative MSE Results of 420 ms-Ahead Predictions for FMLP Models.

Send Rate (Kbps)	FMLP 1			FMLP 2			FMLP 3		
	mean	min	max	mean	min	max	mean	min	max
20Kbps	46.90	18.60	52.07	71.80	63.37	78.15	60.63	55.81	65.54
30Kbps	35.77	12.56	57.07	62.59	35.21	78.75	50.58	33.94	69.79
40Kbps	34.27	16.10	55.08	73.66	34.52	78.86	52.5	23.72	60.48
50Kbps	44.17	31.94	58.25	70.30	35.47	84.63	48.69	18.18	75.10

than FMLP 2 and FMLP 3 models. The performance of FMLP 2 and FMLP 3 models is extremely bad.

From the tables, it can be easily observed that path-independent AR models perform better than path-independent ARMA and FMLP models. Among performance of the AR models, AR 1 model perform best among the developed AR models. Performance of AR 3 model is quite similar to AR 3 model and is acceptable but performance of the AR 2 model is extremely bad for 420 ms prediction horizon.

E. Chapter Overview

This chapter investigates the performance of developed linear and non-linear models on measured traffic data. First part investigates the performance of path-dependent predictors for two source-destination pairs. The SSP of moving average accumulation is accurate. The models gave a good prediction on most of the test cases but MSP is not as accurate as SSP and fails on test cases when the prediction horizon is increased more than 240 ms.

Second part studies the performance of various predictors developed for different paths on one source-destination pair. In case of path-independent predictors, the SSP of the developed predictors is good. However, when the prediction horizon is increased, performance of the developed predictors for different source-destination pairs varies. While one AR predictor developed for different source-destination nodes performed comparable to the predictor developed for the same path , the performance of the other AR predictor is very bad.

So, it can be derived that performance of the path-independent predictors varies a lot and it is advisable to develop predictor for each source-destination nodes. It is observed that AR model performs best in most of the cases especially in cases of MSP and should be preferred over ARMA and FMLP models.

CHAPTER VI

SUMMARY AND CONCLUSIONS

A. Summary

The objective of the present research is to develop predictors for end-to-end single flow characteristics in best-effort networks capable of performing accurate single-step-ahead prediction (SSP) and multi-step-ahead prediction (MSP). The proposed predictors are tested on simulated data generated from network simulator (ns-2). Predictors are also developed and tested using actual traffic data collected from an existing test-bed called the PlanetLab network. In this research, the end-to-end single flow characteristics have been modeled using system identification (SI) techniques involving both linear models as well as neural network based nonlinear models. The linear methods used for modeling are Auto-Regressive (AR) and Auto-Regressive Moving Average (ARMA), whereas the nonlinear method used in this study is a Feed-forward Multilayered Perceptron (FMLP).

In Chapter I, a detailed review of literature used for the research is presented. The literature covers most of the work done in this area including some recent advances made in this field. This chapter provides information on research done in end-to-end flow measurements, estimation, and the use of system identification and artificial neural networks (ANN's) for empirical modeling of network dynamics.

Chapter II gives a detailed description of System Identification techniques used in the research. In this chapter, the linear methods, such AR and ARMA structures, as well as non-linear method, such as FMLP, have been briefly described along with their mathematical equations used.

Chapter III describes the measurement and analysis techniques used for collecting the simulated and the actual traffic data for this research. It explains in detail the type of network topology and setup, bit rate, and the various types of traces collected for simulated as well as actual traffic data. It also discusses various end-to-end network measurements that could be used for developing predictive models. It also describes pre-processing of the data-sets, such as removal of the trend and taking moving average of the signal, before using them for modeling.

In Chapter IV, the various performance metrics used as performance indicators for the prediction are discussed and the prediction results of end-to-end single flow characteristics in a simulated network are presented. The results obtained from various linear and non-linear models are compared. For simulated traffic data, the SSP of moving average time series of accumulation is quite accurate. The developed predictors gave good predictions on most of the cases used for testing. The results of AR, ARMA and FMLP predictors are comparable for SSP. Though not as accurate as the SSP, MSP of moving average time-series accumulation is good till the prediction horizon of 240-ms. However, the developed predictors fails to capture dynamics of the best-effort networks for 420 ms prediction horizon. It is also observed that prediction results are better for end-to-end flow having 20 ms inter-departure time of send packets than flows having 60 ms inter-departure time of the send packets. Hence, it can be concluded that the prediction performance is better when the inter-departure time of the send packets is smaller. For MSP, it was also observed that the AR models perform best among all the developed predictors. The performance of ARMA models for MSP is also comparable to the AR models. The performance of the FMLP models deteriorates much faster when prediction horizon is increased and do not perform as good as AR and ARMA models. Another important thing observed during the prediction of the accumulation signal is the time-shift between the predicted moving average accumulation and actual accumulation. This time-shift is an important factor as timeliness of the prediction is as important as prediction accuracy because of the intended use of the developed predictors.

Chapter V discusses the prediction results of end-to-end single flow characteristics for actual traffic data. This chapter contains two major parts. The first part investigates the performance of the path-dependent predictors for two source-destination pairs. The second part studies the performance of various predictors developed for different paths on a new source-destination pair. The motivation of developing path-independent predictors is to check the feasibility of developing generic predictive models.

The prediction results of the end-to-end single flow characteristics for measured traffic data follows the same trend as the prediction results for simulated traffic data. The SSP of moving average accumulation is quite accurate. The developed predictors gave good predictions on most of the cases used for testing. The variation of the prediction results for data-sets measured during different time of the day are also comparable. That means the developed predictors perform satisfactorily under varying cross-traffic conditions. The results of AR, ARMA and FMLP predictors are comparable for SSP.

Though not as accurate as the SSP, MSP of moving average accumulation is satisfactory till the prediction horizon of 240 ms. However, the developed predictors fails to capture dynamics of the best-effort networks for 420 ms prediction horizon. It is also observed that the prediction performance deters faster compared to the prediction results for the simulated traffic data. For MSP, the prediction performance varies a lot for certain data-sets collected during different time of the day. That means the developed predictors can not perform consistently under different cross-traffic conditions especially when the prediction horizon is increased beyond 240 ms. It also means that there is a lot of unexplained dynamics in the network. It is also observed that the prediction results are better for end-to-end flow having 20 ms inter-departure time of send packets than flows having 60 ms inter-departure time of the send packets. Hence, it can be also concluded that the prediction performance is better when the inter-departure time of the send packets is less.

For MSP, it was also observed that the AR models perform best among all the developed predictors. The performance of ARMA model for MSP is slightly worse than AR model. The FMLP model performance deters much faster and does not perform as good as AR and ARMA models. The time-shift between the predicted and actual accumulation is also observed for the measure traffic data. furthermore, this time-shift increases when the prediction horizon is increased.

For path-independent predictors, different set of predictors for two source-destination pairs are developed. Their performance is then compared with the predictor developed using the same path on which every predictor is tested. For SSP, predictors developed for different source-destination pairs almost perform similar. However, when the prediction horizon is increased, the performance of the predictors developed for different source-destination pairs do not perform as accurate as predictor developed for the same path. While one AR predictor developed for different source-destination nodes performed comparable to the AR predictor developed for the same path , the performance of the other predictors are very bad. Hence, it is advisable to develop source-destination specific predictors.

B. Conclusions and Recommendations

The proposed approach in this study has a direct impact on the end-to-end single flow characteristics. Empirical models like these can be used in developing effective network control strategies which can lead to improved QoS of non-interactive and interactive real-time multimedia applications like audio. The following paragraphs outlines various conclusions drawn during the prediction of simulated as well as actual traffic data.

The following are the conclusions drawn from this study:

1. The use of linear system identification techniques and neural networks as non-linear model structures to identify the end-to-end single flow characteristics in a best-effort network, such as an Internet, seems possible. Network measurements can be used to obtain empirical models to predict the end-to-end flow behavior.

2. It is observed in this study that SSP is much more accurate than MSP. It has also been observed the deterioration of the prediction results are very fast when prediction horizon is increased beyond 240 ms. The developed predictors perform accurately for different source send rate.

3. It is observed that AR model performs best in most of the cases and it should be preferred over ARMA and FMLP models for end-to-end single flow prediction in best-effort network.

4. It is observed that the predictors developed for each end-to-end path perform better on that particular path than the predictors developed for different end-to-end paths.

The following recommendations are proposed for further research in this area:

1. Further optimization of the MSP results is necessary, as MSP is needed to produce a flow prediction within a finite future prediction horizon.

2. Effectiveness of the neural network structures, such as Recurrent multi-layer perceptron, and some other pattern identification techniques should be investigated for predicting end-to-end flow characteristics.

3. Empirical models have to be developed to model closed-loop network dynamics of applications using TCP as the transport protocol.

4. Predictive controllers needs to be developed to gauge the effectiveness of the empirical models for flow control and their impact on improving the end-to-end QoS.

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